AN EXAMINATION OF IDIOSYNCRATIC VOLATILITY IN AUSTRALIA

By

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DECLARATION OF ORIGINALITY

I certify that except where due acknowledgement has been made, this thesis is the original work of the author alone. The thesis has not been submitted previously, in whole or in part, to qualify for any other academic award. The content of thesis is the results of work which has been carried out since the official commencement date of approved research program; and any editorial work, paid or unpaid, carried out by a third party is acknowledged.

Signature:

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February 2014

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ABSTRACT

In finance, the pricing of assets is an area of fundamental importance. Many theories and their associated models have been proposed. The Capital Asset Pricing Model is arguably the most important of these as it provides the basis for many other asset pricing models. The theory of the Capital Asset Pricing Model states that investors should be compensated for higher systematic risk taken but should not be compensated for higher unsystematic risk or idiosyncratic volatility taken. The reason for this is that the Capital Asset Pricing Model suggests that idiosyncratic volatility should be ignored since investors are assumed to hold proportions of the well diversified market portfolio. Therefore, idiosyncratic volatility is fully diversified away in their portfolios and only systematic risk should be priced. However, it is not realistic to assume that every investor holds a proportion of the well diversified market portfolio in the real world because of market imperfections such as transaction costs and/or limited knowledge in all securities. Hence, idiosyncratic volatility should not be ignored in the area of asset pricing.

This thesis explores the asset pricing role of idiosyncratic volatility by using the portfolio risk mimicking approach of Fama and French (1993) to construct an idiosyncratic volatility factor and tests whether this idiosyncratic volatility factor is priced for the returns of Australian stocks and pension funds. The results show that the idiosyncratic volatility factor is priced for both returns of Australian stocks and pension funds.

Given the strong evidence found to support the notion that idiosyncratic volatility is important in pricing Australian stock returns and pension fund returns, this thesis further explores the factors which explain idiosyncratic volatility by investigating the cross-sectional relationship between idiosyncratic volatility and stock fundamental ratios.

Finally, this thesis investigates whether the risk mimicking asset pricing factors, including the idiosyncratic volatility factor, predict the growth rate of the Australian economy in the context of Liew and Vassalou (2000) models. It is found that the risk mimicking asset pricing factors can be used to predict the growth rate of the Australian economy.

CHAPTER 1

1. INTRODUCTION

1.1. BACKGROUND

The risk of a portfolio comprises systematic risk and unsystematic risk. Systematic risk cannot be diversified as it is the risk common to all risky assets. Unsystematic risk, also known as idiosyncratic volatility, is firm specific, so it can be diversified away by holding sufficient number of risky assets in a portfolio.

In finance, the pricing of assets is an area of fundamental importance. Many theories and their associated models have been proposed. In general, these theories map the relationship between risk and return. The Capital Asset Pricing Model (hereafter CAPM) developed by Sharpe and Lintner is arguably the most important of these as it provide the basis for many other asset pricing models. Importantly, assumptions of CAPM are still regarded as the backbone of most modern theories. Specifically, the theory of CAPM states a positive relationship between return of risk assets and systematic risk. According to CAPM, investors should be compensated for assuming higher systematic risk but should not be compensated for assuming higher idiosyncratic volatility. The reason for this is that CAPM suggests idiosyncratic volatility should be ignored since investors are expected to hold proportions of the well diversified market portfolio. Hence, idiosyncratic volatility is fully diversified away and only systematic risk should be priced. However, it is not realistic to expect that every investor holds a proportion of the well diversified market portfolio. In reality, investors do not hold well diversified portfolios, for example Goetzmann and Kumar (2004) show that more that 25% of investors hold only one stock and less than 10% of the investors hold more than 10 stocks, while Campbell et al. (2001) suggest that in order to achieve diversification investors must hold at least 50 randomly selected stocks in their portfolio.

If investors do not hold fully diversified portfolios in the real world, then pricing of idiosyncratic volatility becomes an issue of major importance. Merton (1987) suggests that investors should be compensated for holding underdiversified portfolios. Therefore, the pricing of idiosyncratic volatility has attracted increasing attention from researchers since late 1990's.

Recent empirical research in the pricing of idiosyncratic volatility reports mixed results. Both positive and negative significant relationships between returns of risky assets and idiosyncratic volatility have been found. For example, Malkiel and Xu (1997, 2006), Goyal and Santa-Clara (2003) and Fu (2009) find idiosyncratic volatility is significantly and positively related to US stock returns, whereas Ang, Hodrick, Xing and Zhang (2006, 2009) find a negative relationship between lagged idiosyncratic volatility and future average returns in the US and other developed countries including Australia. In contrast, Bollen, Skotnicki and Veeraraghavan (2009) find that there is no significant relationship between idiosyncratic volatility and stock returns in Australia. Generally, despite the inconsistent findings across markets, most agree that idiosyncratic volatility is an omitted pricing factor by CAPM.

1.2. MOTIVATION FOR STUDYING IDIOSYNCRATIC VOLATILITY IN AUSTRALIA

The pricing of idiosyncratic volatility and the role of idiosyncratic volatility in the financial markets are not intensively researched because CAPM suggests that idiosyncratic volatility should be ignored as it is fully diversified by holding a proportion of the well diversified market portfolio.

However, Goetzmann and Kumar (2004) and Campbell et al. (2001) indicate that in reality investors do not hold well diversified portfolios due to a number of factors including transaction costs and investors' limited knowledge of securities. In addition, some researchers find CAPM fails in the real world applications. For example, Fama and French (1992) find that CAPM failed to explain stock returns over a 27 year period extending from 1963 to 1990 as the systematic risk proxy-Beta was not related to the returns. These studies have motivated researchers to turn their attention back to the asset pricing role of idiosyncratic volatility because, (1) idiosyncratic volatility may not be fully diversified away in the portfolios, (2) it is unrealistic to assume that every investor holds a proportion of the well diversified market portfolio, and (3) idiosyncratic volatility could be an omitted factor in asset pricing models.

Recent studies in the area of idiosyncratic volatility focus on its asset pricing role, but the relationship between idiosyncratic volatility and returns is not yet clear. This is not surprising since different measurements of idiosyncratic volatility and different data have been used in the studies. Without testing these measurements of idiosyncratic volatility in one study, it is hard to conclude which measurement is the best under what conditions.

However, at this stage, the most important research task is not to compare and evaluate different measurements of idiosyncratic volatility as idiosyncratic volatility hasn't been investigated intensively. Instead, it is more important to further explore the asset pricing role of idiosyncratic volatility. In order to explore and understand the asset pricing role of idiosyncratic volatility better, this thesis is motivated to develop a new measurement for idiosyncratic volatility. This new measurement of idiosyncratic volatility provides a clearer insight into roles of idiosyncratic volatility from a different angle.

Therefore, the main purpose of this thesis is to test whether idiosyncratic volatility is priced in the returns of Australian stocks and pension funds by using a new idiosyncratic volatility measurement, then further explore the predictability of idiosyncratic volatility to major economic indicators and the factors explain idiosyncratic volatility.

To date, the majority of studies in the area of asset pricing and idiosyncratic volatility focus on the relationship between risky asset returns and idiosyncratic volatility in the US markets. There is lack of research in the area using Australian data. Therefore, this thesis attempts to examine the roles of idiosyncratic volatility in Australia, because Australia has some of the most important financial markets in the world. For example, according to MSCI global index ranking the Australian stock market is ranked the eighth largest stock market in the world as at 31 August 2012, by market capitalisation[1]. Therefore, this thesis is motivated to explore the roles of idiosyncratic volatility in one of the most important financial markets globally that has not, to date, been investigated in a significant way.

[1] http://www.asxgroup.com.au/the-australian-market.htm

This thesis provides solid evidence to support the notion that idiosyncratic volatility plays a significant role in Australian equity markets. Therefore, it should not be ignored but instead should be considered when evaluating the performance of Australian stock portfolios and pension funds. It can also be used to predict Australian economic conditions.

1.3. OBJECTIVES OF THE THESIS

There are four objectives of this investigation:

1. To investigate whether idiosyncratic volatility matters in the pricing of Australian stock returns. Following Ang, Hodrick, Xing and Zhang (2006, 2009), idiosyncratic volatility is defined and estimated. A new idiosyncratic volatility mimicking factor (hereafter idiosyncratic volatility factor) is developed and tested in the presence of Fama and French three-factor by using regression analysis. The time series relationship between the idiosyncratic volatility factor and Australian stock returns is investigated by using 25 size and book-to-market portfolios and ten idiosyncratic volatility portfolios. The cross-sectional relationship between the idiosyncratic volatility factor and Australian stock return is investigated by using Fama and Macbeth cross-sectional regressions. Both time series regressions analysis and cross-sectional regression analysis show that the idiosyncratic volatility factor is an omitted asset pricing factor for Australian stocks.
2. To investigate whether idiosyncratic volatility matters in the pricing of Australian pension funds. Conventional wisdom suggests that pension funds are supposed to be well diversified, so idiosyncratic volatility should have no role in explaining pension

fund returns. However, Campbell et al. (2001) suggest that idiosyncratic risk increased over time, implying that investors should increase the number of securities in their portfolio in order to maintain the same level of diversification over time. Failing to do this would lead to the increase in idiosyncratic volatility of their portfolios. In order to investigate the effect of idiosyncratic volatility in pricing Australian pension funds, time series regressions are employed to analyse the relationship between idiosyncratic volatility and Australian pension fund returns. The empirical results suggest that idiosyncratic volatility is important in the pricing Australian pension fund returns, especially in the pricing of Australian equity pension fund returns.

3. To explore what factors might explain idiosyncratic volatility in Australia. As idiosyncratic volatility is firm specific, firm specific information should relate to idiosyncratic volatility. Using six stock fundamental ratios as proxies for firm specific information, the empirical results show that there is a significant positive cross-sectional relationship between dividend yield and the idiosyncratic volatility and a significant negative cross-sectional relationship between price to earnings ratio, ROE and the idiosyncratic volatility.
4. To investigate whether the asset pricing factors, including the idiosyncratic volatility factor, contain information in regard to future Australian economy growth. Some previous studies report that stock market information can be used to predict economic growth. For example, Liew and Vassalou (2000) find that asset pricing factors as important sources of stock market information predict economic growth. In this thesis, the empirical results show strong evidence to support the notion that

idiosyncratic volatility is an omitted asset pricing factor by CAPM and the Fama and French three-factor model. Therefore, idiosyncratic volatility as an asset pricing factor may also contain information about future economic growth. Using the Liew and Vassalou (2000) model by adding an idiosyncratic volatility factor, the empirical results suggest that the asset pricing factors predict the growth rate of Australian economy.

1.4. STRUCTURE OF THE THESIS

This thesis is organized as follows. Chapter 2 reviews the most relevant literature in the areas of idiosyncratic volatility, asset pricing, the relationship between idiosyncratic volatility and stock fundamental ratios and the predictability of asset pricing factors to future economy growth. Chapter 3 investigates the pricing of idiosyncratic volatility for Australian stock returns by extending the Fama and French three-factor model in an Australian context. A new idiosyncratic volatility factor is developed and tested in the presence of Fama and French's three factors. This chapter addresses the question of whether the idiosyncratic volatility factor is an omitted asset pricing factor for Australian stocks. Chapter 4 investigates the pricing of idiosyncratic volatility for Australian pension funds. A new pension fund size mimicking factor is also developed and tested in the chapter. Chapter 5 explores the factors that explain idiosyncratic volatility in Australian equity markets. Stock fundamental ratios are used as proxies for the firm specific information, and the empirical results provide strong evidence to support that idiosyncratic volatility is related to the firm specific information. Chapter 6 explores the predictability of the asset pricing factors to Australian economy growth by extending the Liew and Vassalou (2000) model.

Chapter 7 concludes this thesis by summarizing the major findings and outlining future research directions.

1.5. CONTRIBUTIONS OF THE THESIS

This thesis examines four idiosyncratic volatility related issues in Australia. The four issues are investigated in Chapter 3 to 6.

Chapter 3 investigates the issue that whether idiosyncratic volatility matters in the pricing of Australian stock returns. This chapter contributes to the literature in several ways: (1) the pricing of idiosyncratic volatility is investigated in this chapter by using a different proxy of idiosyncratic volatility compared to those of previous studies. An idiosyncratic volatility mimicking factor is constructed by following the portfolio risk mimicking approach of Fama and French (1993); (2) the majority of studies in this area focus on the US and as such there is a significant lack of attention to Australian data. Therefore, this study provides a unique insight into one of the most important global financial markets; (3) it is not clear that idiosyncratic volatility is priced in the Australian stock market, nor what the effect of idiosyncratic volatility is on Australian stocks with different size and book-to-market equity ratio. This chapter also investigates the effects of idiosyncratic volatility in the pricing of 25 stock portfolios sorted on size and book-to-market equity ratio.

Chapter 4 investigates the issue of whether idiosyncratic volatility matters in the pricing of Australian pension fund returns. To the author's knowledge, this is the first study that investigates the effects of idiosyncratic volatility in the pricing of Australian pension fund returns. In this chapter, a fund size factor and an idiosyncratic volatility factor are constructed by following the portfolio rick mimicking approach of Fama and French (1993) to mimic the risks associated with fund size and idiosyncratic volatility. The results provide insights to whether the fund specific risk mimicking factors capture the variation in the return of Australian pension funds.

Chapter 5 contributes to the literature by exploring the driving factors of idiosyncratic volatility in Australia. The empirical results from Chapter 3 and 4 strongly support that idiosyncratic volatility matters in the pricing of the returns of Australian stocks and pension funds, so this study is further motivated to explore the driving factors of idiosyncratic volatility in Australia. Previous studies find evidence to support that proxies of firm specific information, such as stock fundamental ratios, explain idiosyncratic volatilities in the US and Japan, but to the author's knowledge, there is no Australian study in this area. Moreover, previous studies have focused on the role of profitability ratios in explaining idiosyncratic volatility but the role of ratios relating to other stock fundamentals, such as leverage and valuation, have not been investigated. Therefore, this chapter expands the literature by (1) investigating the relationship between idiosyncratic volatility and stock fundamental ratios by using Australian data; and (2) using the ratios from three major areas of stock fundamentals, namely profitability ratios, leverage ratios and valuation ratios.

Chapter 6 contributes to the literature in two major ways. Frist, this chapter investigates the issue of whether idiosyncratic volatility is a state variable in the context of Merton (1973) by augmenting an idiosyncratic volatility factor to the regression model of Liew and Vassalou (2000). Second, previous studies find stock market factors predict GDP growth rate, but it is not clear whether stock market factors predict other aspects of the economy. This chapter addresses this issue by expanding the set of economic variables to ten major economic indicators. These ten economic indicators represent different aspects of Australian economy.

Overall, this thesis provides an insight into the different roles of idiosyncratic volatility in regard to different important issues in Australia. Strong and consistent results are presented in Chapter 3 to 6 to support that idiosyncratic volatility really matters in Australia.

CHAPTER 2

2. LITERATURE REVIEW

2.1. INTRODUCTION

CAPM predicts the required rate of return for a risky asset given the asset's systematic risk. The model only takes into account systematic risk. Unsystematic risk is ignored by the model since unsystematic risk is assumed to be diversified away as a result of investors holding proportions of the well diversified market portfolio. In reality, however, this is not always the case. Several studies have identified that for various reasons, investors do not always hold well-diversified portfolios (see example Malkiel and Xu, 2006; and Goetzmann and Kumar, 2004), and therefore systematic risk is an incomplete explanation of risk factors to be considered when modelling returns. Merton (1987) suggests that investors are compensated for holding underdiversified portfolios. The question of whether or not idiosyncratic volatility is priced has therefore attracted increasing attention amongst researchers in this area.

The importance of idiosyncratic volatility was ignored until the late 1990's. The role of idiosyncratic volatility in asset pricing was first reported by Malkiel and Xu (1997). Malkiel and Xu (1997) find that idiosyncratic volatility is priced for US stocks returns. Since then idiosyncratic volatility has drawn the attention of a number of researchers. Majority of studies in this area support that idiosyncratic volatility is priced for risky asset returns, but the relationship between idiosyncratic volatility and returns is not clear as mixed results have been reported. For example, Malkiel and Xu (1997, 2006), Goyal and

Santa-Clara (2003), Fu (2009) find a positive relationship between idiosyncratic volatility and returns in the US, while Ang, Hodrick, Xing and Zhang (2006, 2009) find a negative relationship between idiosyncratic volatility and returns in the US.

The majority of previous studies suggest that idiosyncratic volatility is important when considering factors of asset pricing. Some further issues in regard to idiosyncratic volatility have also attracted researchers' attention. These issues include: (1) what factors explain idiosyncratic volatility, and (2) the information contained within idiosyncratic volatility in relation to growth rate of future economy. Only a few studies have attempted to address these issues in the US and Japan (see example Liew and Vassalou, 2000; Wei and Zhang, 2004; Brown and Kapadia, 2005; and Chang and Dong, 2006). There is no known studies of the Australian equity market.

This chapter summarizes previous research investigating idiosyncratic volatility. The studies most relevant to this thesis are discussed in Section 2.2. Section 2.3 summarizes a number of studies that investigate the pricing of idiosyncratic volatility for risky asset returns. Section 2.4 reviews studies that explore the factors that explain idiosyncratic volatility. Section 2.5 outlines the studies that investigate the information content of the asset pricing factors. The conclusion for this chapter is presented in Section 2.6.

2.2. KEY STUDIES

The analysis undertaken in this thesis is motivated by several key studies.

2.2.1. Fama and French (1992, 1993)

Fama and French (1992) reports that size and book to market equity ratio (hereafter BE/ME) explain the average returns of NYSE, Amex and NASDAQ stocks for the period of 1963 to 1990. They find that high (low) BE/ME stocks tend to have low (high) persistent earnings on assets. They also find that size is related to profitability as small firms tend to have lower earnings on assets after controlling for BE/ME. Moreover, they find that size and BE/ME are related to economic fundamentals. Therefore, they suggest that size and BE/ME proxy common risk in returns. The evidence reported in the study suggests that size and BE/ME proxy different dimensions of stock risks and this subsequently leads to the development of the Fama and French (1993) three-factor model. The success of the Fama and French three-factor model indicates that common risk factors other than the market risk factor are omitted by CAPM and could therefore have significant explanatory power to asset returns.

Fama and French (1993) use time series regression analysis to explore whether size and BE/ME are proxies for common risk factors in returns. They sort stocks into six portfolios based on size and BE/ME to mimic the underlying risk in returns related to size and the book-to-market equity. More specifically, all stocks are ranked according to size then divided into two portfolios - small and big. Then, all stocks are ranked and sorted into three book-to-market equity portfolios. Consequently, six portfolios are constructed by using the intersections of two size portfolios and three BE/ME portfolios. After six size and BE/ME portfolios are constructed, the size mimicking factor is calculated as the returns of small stock portfolios minus the returns of big stock portfolios and the BE/ME mimicking factor is calculated as the returns of high BE/ME portfolios minus the returns of low BE/ME portfolios. The size factor is meant to mimic the risk associated with returns related to size, and the BE/ME factor is meant to mimic the risk associated with returns related to BE/ME.

Fama and French (1993) find that the market factor, size mimicking factor (hereafter size factor) and book-to-market equity ratio mimicking factor (hereafter BE/ME factor) capture strong variations in stock returns, but these factors do not capture much variation in the returns alone. More interestingly, the coefficients of the market factor are close to 1 in regressions that include the size factor and the BE/ME factor but there are trends in the coefficients of size and BE/ME factors when moving from big size to small size portfolios, and the high book-to-market equity ratio portfolio to the low book-to-market equity ratio portfolio. Thus, the variations in returns are captured by size factor and BE/ME factor.

Therefore, Fama and French (1993) report strong evidence supporting the notion that their three-factor model explains greater variations in stock returns than the one factor CAPM model. Risk mimicking factors, such as the size factor and the BE/ME factor, are omitted by the one factor asset pricing model.

2.2.2. Ang, Hodrick, Xing and Zhang (2009)

Finance theory suggests that there is positive relationship between risk and return because investors require a higher rate of return to compensate higher risk. For example, Merton (1987) suggests that investors may not be able to form well-diversified portfolios due to high transaction costs and limited knowledge of risky assets. Therefore, investors require higher rates of return for holding under-diversified portfolios in order to compensate the existing idiosyncratic volatility in their portfolios. However, empirically Ang, Hodrick, Xing and Zhang (2009) find a negative relationship between lagged idiosyncratic volatility and future stock returns in 23 developed markets. This finding is inconsistent with Merton's proposition.

Ang, Hodrick, Xing and Zhang (2009) define idiosyncratic volatility as the standard deviation of the regression residual from the Fama and French three-factor regression model. They argue that idiosyncratic volatility contains information missed by the Fama and French three-factor model. Their study contributes to the literature by showing significant negative relationships between lagged idiosyncratic volatility and future stock returns in 23 developed countries, especially in the G7 countries (Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom). They suggest that the negative relationship between idiosyncratic volatility and stock returns is an international phenomenon. However, the negative idiosyncratic volatility-return relationship is hard to explain in theory. They call this negative relationship a puzzle. They attempted to explain this puzzle by controlling the effects of transaction costs, private information, analyst coverage, institutional ownership, delay in price responses to information, but none of these factors explained the puzzle sufficiently.

2.2.3. Drew, Naughton and Veeraraghavan (2004)

Drew, Naughton and Veeraraghavan (2004) construct an idiosyncratic volatility mimicking factor using the mimicking portfolio approach of Fama and French (1996). They find that the idiosyncratic volatility mimicking factor is priced for stocks listed in the Shanghai Stock Exchange from 1993 to 2000.

One of the major contributions to the literature made by this study is the development of an idiosyncratic volatility mimicking factor. In this study, idiosyncratic volatility is defined as the difference between the variance of returns and the beta of a stock multiplied by the variance of the stock market index. Variance of returns is a proxy for total risk of a stock and beta of a stock multiplied by the variance of the stock market index is a proxy for systematic risk. Therefore, idiosyncratic volatility is measured as the difference between total risk of a stock and the systematic risk.

After the idiosyncratic volatility of the stocks is calculated, they follow Fama and French (1996) to construct six portfolios sorted by size and idiosyncratic volatility. First, stocks are sorted into two size portfolios and then stocks in each size portfolio are sorted into three idiosyncratic volatility portfolios. Following this, an idiosyncratic volatility mimicking factor is constructed as the average returns of the two high idiosyncratic volatility portfolios minus the average returns of the two low idiosyncratic volatility portfolios. A size factor is constructed as the average returns of the three small stock portfolios minus the average returns of the three big portfolios.

After the size factor and the idiosyncratic volatility factor are constructed, this study explores whether returns of the stocks can be explained by a market factor, the size factor and the idiosyncratic volatility mimicking factor. The empirical results of this study shows that the idiosyncratic volatility is priced for the stock returns over the sample period suggesting that idiosyncratic volatility plays an important role in asset pricing.

Since Drew, Naughton and Veeraraghavan (2004) find strong evidences to support that an idiosyncratic mimicking factor plays important role in explaining stock returns. The development of idiosyncratic volatility mimicking factor expands the literature in the area of asset pricing factors.

However, the regression model and definition of idiosyncratic volatility of Drew, Naughton and Veeraraghavan (2004) are not conservative because the BE/ME factor is not presented in their models. Therefore, one contribution of this thesis is the construction of a new idiosyncratic volatility mimicking factor by using a different but widely accepted definition for idiosyncratic volatility and subsequently examining the explanatory power of the idiosyncratic volatility mimicking factor to risky asset returns in Australian equity market.

2.2.4. Liew and Vassalou (2000)

Stock prices reflect investors' expectations on future earnings of companies, and earnings of companies are highly correlated with the growth rate of the economy. In general, investors expect that stock prices will rise in the case that economy is expected to grow at faster rate in the future[2]. Hence, there is possibility that stock market information predicts the short term economic growth rate. Stock prices contain information about future economic growth.

Liew and Vassalou (2000) use the return based asset pricing factors, such as a market factor, a size factor, a BE/ME factor and a momentum factor, as proxies for the stock market information and investigate whether these factors predict economic growth for ten developed countries from 1978 to 1996. They find that the size factor and the BE/ME

[2] The exception is that there is downward pressure on asset prices when economy is overheating.

factor are related to the future growth of the economy, but they found little evidence to establish a relationship between the momentum factor and the future growth of the economy. Their empirical results also show that the size factor and the BE/ME factor contain different information about future GDP growth than the market factor. They suggest that the size factor and the BE/ME factor are state variables in the context of Merton (1973) as they find a positive relationship between the two return based asset pricing factors and the future growth of the economy.

Liew and Vassalou (2000) contributes to the literature by providing empirical evidence to support that there is a relationship between return based asset pricing factors and economy growth rate. They use GDP growth rate to represent the growth rate of the economy. As GDP growth rate only represents one aspect of the economy[3], this thesis expands the set of proxies for the economy by using ten major economic indicators. Empirical results from Chapter 3 and 4 show that the idiosyncratic volatility mimicking factor is an important asset pricing factor for Australian risky assets, so that the idiosyncratic volatility mimicking factor is tested for its information content about future growth of the economy in Chapter 6.

2.2.5. Chang and Dong (2006)

The role of idiosyncratic volatility in the market is becoming more and more important as several studies in the area find strong evidence to support that idiosyncratic volatility increases over time (see examples, Campbell, Lettau, Malkiel and Xu, 2001, Malkiel and

[3] GDP growth rate represents the growth rate in total values goods and services over a period.

Xu, 2003 and Wei and Zhang, 2004). The important implication for increasing idiosyncratic volatility is that investors may need to increase the number of stocks in their portfolio over time in order to maintain the same level of diversification. However, it is not clear what factors drive idiosyncratic volatility over time.

As suggested by Vuolteenaho (2002), cash flow information drives firm-level returns. Both cash flow information and firm-level returns are firm specific. Vuolteenaho (2002) argues that cash flows and returns are related to the stock fundamental ratio that may explain idiosyncratic volatility. Chang and Dong (2005) explore the cross-sectional relationship between two profitability ratios, specifically return of assets (hereafter ROA) and return of equity (hereafter ROE), and idiosyncratic volatility in Japan from 1975 to 2003. They find that idiosyncratic volatility can be explained by these profitability ratios, and firms with either high earnings or low earrings tend to have high idiosyncratic volatility. Their study suggests that there are possible links between idiosyncratic volatility and stock fundamental ratios.

2.3. SYSTEMATIC RISK, IDIOSYNCRATIC VOLATILITY AND RISKY ASSET RETURNS

A good starting point is CAPM. CAPM is based on the theoretical framework developed by Markowitz (1959). In Markowitz's model, it is assumed that the mean-variance trade-off is the only factor that investors should be concerned about. Investors' decisions for portfolio selection are based on either minimizing the variance of portfolio returns given an expected return or maximizing expected returns given the variance of portfolio returns. Subsequently, two key assumptions are added by Sharpe (1964) and Lintner (1965), leading to the development of CAPM. CAPM assumes that the market portfolio is mean-variance efficient. The implication of CAPM is that only market risk is priced, thus idiosyncratic volatility has no power in explaining the returns of assets.

Many researchers suggest that CAPM is simple and general, failing in its practical application because of its over-simplified assumptions. The main findings in the area of asset pricing following the late 1970’s suggest explanatory variables other than the systematic risk factor contain information about the expected return. In addition, some researchers report several other factors have explanatory power for returns. For example, Basu (1977) reports future returns on high Earnings/Price (hereafter E/P) stocks are higher than the returns estimated by CAPM. Banz (1981) finds small stocks earn higher returns than estimated by CAPM. Statman (1980) finds that stocks with a high book-to-market equity ratio have high average returns that CAPM fails to capture. Rosenberg, Reid and Lanstein (1985) find that BE/ME plays an important role in explanation of expected returns. Merton (1987) suggests that idiosyncratic volatility should be priced. He argues that investors may not have complete information for every stock. Therefore, these investors hold underdiversified portfolios because they form portfolios from the known stocks which represent small subset of the total stocks available.

In the early 1990’s, researchers reported additional explanatory factors for returns. For example, Fama and French (1992) find that size, E/P, debt to equity ratio and BE/ME explain US stock returns. They suggest that size, and BE/ME are pricing factors for returns, so these variables proxy different dimensions of stock risks. This subsequently led to the development of the Fama and French (1993) three-factor model. Fama and French (1993) developed a three-factor model that captures most of variation of US stock returns. Fama and French (1996) find similar results as Fama and French (1993) by using a time series regression approach. They have provided further evidence to support that the market factor, the size factor and the BE/ME factor contain information about returns. Fama and French (1998) find that the three-factor model is not sample specific as results were consistent across of twelve non-US major markets. The success of the Fama and French three-factor model indicates that risk factors other than the market risk factor omitted by CAPM could have significant explanatory power to the asset returns.

The Fama and French three-factor model has been tested in the Australian equity market. Drew and Veeraraghavan (2002) find that the Fama and French three-factor model explains the variation of Australian stock returns. Gaunt (2004) finds that the Fama and French three-factor model captures much more variation in equity returns than CAPM, and both the size factor and the book-to-market factor play important roles in asset pricing. Faff (2004) tested the Fama and French three-factor model by using daily data and the generalized method of moments technique and their results support the Fama and French three-factor model.

The success of the Fama and French three-factor model gives some indication that risk factors omitted by CAPM could play an important role in asset pricing. In theory, CAPM assumes that every investor holds a proportion of the fully diversified market portfolio, so that the investors are compensated for the systematic risk they've taken. By definition, idiosyncratic volatility is the unsystematic risk which is not captured by the market risk factor. According to theory underlying CAPM, idiosyncratic volatility is not priced because the market portfolio is fully diversified and every investor is assumed to hold a proportion of the fully diversified market portfolio, so that only systematic risk is priced for returns of risky assets. However, this assumption is not realistic in the real world.

In reality not every investor holds fully diversified portfolios. Individual investors are not likely to hold well-diversified portfolios due to a number of reasons, including transaction costs, information costs and choice of investment style. When considering transaction costs, for example, individual investors are reluctant to increase the level of diversification of their portfolios if they believe the transaction costs are greater than the benefits associated with further diversification.

Further, information is costly, so it is impossible for individual investors and even institutional investors to collect and analyse all information about all securities in the market in a timely manner. Consequently, investors only have information for a subset of all securities and they construct portfolios heavily weighted in these securities. The outcome is that they hold under-diversified portfolios. In some cases, investors are speculators who are willing to speculate on forthcoming information. These investors deliberately hold under-diversified portfolios as they expect high future returns to compensate the high idiosyncratic volatility they assume.

Finally, investment style may also lead to investors holding less than fully diversified portfolios. Campbell et al. (2001), for example, suggest that many individual investors hold a few stocks due to the restrictions of corporate compensation plans. Goetzmann and Kumar (2004) report that more that 25% of investors hold only one stock and less than 10% of the investors hold more than 10 stocks, while Campbell et al. (2001) suggest that in order to achieve diversification investors must hold at least 50 randomly selected stocks in their portfolio. These studies support the notion that many investors do not hold well diversified portfolios and idiosyncratic volatility is not fully diversified in their portfolio.

As mentioned above, previous literature suggests that CAPM is based on unrealistic assumptions. For example, Merton (1987) suggests that the assumptions underlying financial models are inadequate. He suggests that “financial models based on frictionless markets and complete information is often inadequate to capture the complexity of rationality in action”. This suggestion is highly likely to be true because, in reality, investors’ behaviour is not always rational and markets are not frictionless. Hence, investors do not always have complete information and it’s not optimal for every investor to study every security available in the market. Therefore, many investors construct their portfolios based on stocks which they know. Compared to the total number of stocks available, investors usually know only a small subset. The final result is that many investors hold under-diversified portfolios. In addition, Bollen, Skotnicki and Veeraraghavan (2009) suggest that some portfolio managers do not hold well diversified portfolios due to contractual reasons or their investment style. The implication is that market risk is not the only risk to be priced. Unsystematic risk, such as idiosyncratic volatility, should also be priced.

The association between idiosyncratic volatility and stock returns was identified during the 1970’s and the 1980’s (see example Friend, Westerfield and Granito, 1978; Levy. 1978; and Amihud and Mendelson, 1989). Idiosyncratic volatility has attracted additional attention since the 1990’s. Malkiel and Xu (1997), for example, find that idiosyncratic volatility is priced for returns of US stocks and the market factor has little power in explaining the risk-return relationship. They suggest that portfolio managers are forced to buy/sell stocks by the directors when they are changing in prices. Hence, portfolio managers require additional returns for the idiosyncratic volatility they assume.

Campbell et al. (2001) summarize the historical movements in market, industry and idiosyncratic firm level risk. Campbell et al. (2001) find that idiosyncratic firm level risk increased from 1962 to 1997 by using a disaggregated approach to study the risk of stocks at the market, industry and idiosyncratic firm level. They find that aggregate market volatility has been stable but idiosyncratic volatility has increased over the sample period. The results suggest that the correlation among individual stocks declined over the sample period which implies that the number of stocks required to achieve a given level of diversification has increased. They also suggest that market level, industry and firm-level risk increases during economic downturns, especially firm-level risk. The implication is that if investors are to be fully diversified they must increase the number of stocks in their portfolio during an economic downturn.

Idiosyncratic volatility has drawn the attention of a number of researchers since the late 1990's. For example, Malkiel and Xu (1997) find that idiosyncratic volatility is priced for US stocks returns. Campbell et al. (2001) reports that idiosyncratic volatility increased from 1962 to 1997 in the US. Goyal and Santa-Clara (2003) find a positive relationship between average stock variance (largely idiosyncratic) and portfolio returns on the NYSE/AMEX/NASDAQ stocks from 1963 to 1999. They argue that the holding of non-tradable assets by investors adds risk to their tradable portfolio decisions. When risk of non-traded assets increases, investors are less likely to hold risky tradable assets and then require higher expected return in order to compensate them for the increase in risk. Bali et al. (2005) replicated the study by Goyal and Santa-Clara (2003) and show that a positive relationship exists between idiosyncratic volatility and returns. They suggest that the positive relationship between idiosyncratic volatility and returns is driven by small stocks on NASDAQ. However, this positive relationship does not hold for NYSE stocks. Their results indicate that the effect of idiosyncratic volatility is more pronounced in small stocks. Fu (2009) reports a positive relationship between expected idiosyncratic volatility and returns of stocks traded on NYSE, Amex and NASDAQ from 1963 to 2006. Guo and Savickas (2010) find a significant positive relationship between idiosyncratic volatility and cross-sectional US stock returns by utilizing an IVF factor. They define the IVF factor as the difference between returns of low and high CAPM based idiosyncratic volatility stocks. They also find that the explanatory power of IVF factor is weaker for low idiosyncratic volatility stocks than high idiosyncratic volatility stocks because high idiosyncratic volatility stocks are more sensitive to discount rate shocks. These studies support that there is positive relationship between idiosyncratic volatility and returns.

However, contrary results in regard to the relationship between idiosyncratic volatility and returns are found by Ang et al. (2006, 2009) in their analysis of realized idiosyncratic volatility. Their findings indicate that lagged realized idiosyncratic volatility is negatively related to the stock returns in the US and other developed countries, and they suggest that there is an unidentified economic source which drives the relationship between idiosyncratic volatility and return. Person and Smedema (2011) confirm the empirical results of Ang et al. (2006, 2009) and Fu (2009) and find that there is significant negative relationship between realized idiosyncratic volatility and US stock returns in non-January months and significant positive relationship between expected idiosyncratic volatility and US stock returns respectively. They report that both idiosyncratic volatilities are strongly related to US stock returns and the negative relationship between realized idiosyncratic volatility and returns depends on aggregate investor sentiment as they suggest that investors sell accurately valued stocks in month t-1 and buy overvalued stocks in month t. Hence, a negative return can be seen in month t with stocks that have high realized idiosyncratic volatility in month t-1.

While a number of previous studies focus on the US market, there are only a few published papers to date that investigate the effect of idiosyncratic volatility on the pricing of Australian assets. Bollen, Skotnicki and Veeraraghavan (2009) follow the idiosyncratic volatility estimation method of Campbell et al. (1997) and find that idiosyncratic volatility is not priced in the Australian stock market. Brockman, Schutte and Yu (2009) employ the idiosyncratic volatility estimation method of Fu (2009), and examine the idiosyncratic volatility in the pricing of stocks in 44 countries including Australia. They report a significant positive relationship between expected idiosyncratic volatility and Australian stock returns. Despite a few studies having investigated the Australian market, the role of idiosyncratic volatility in pricing of Australian stocks is not well understood.

The role of idiosyncratic volatility in asset pricing has been tested with different classes of assets. Ooi, Wang and Webb (2009) examine the importance of idiosyncratic volatility in the pricing of real estate investment trust (hereafter REIT) stocks and find a significant positive relationship between expected idiosyncratic volatility and the time-series returns. In addition, they find that idiosyncratic volatility of REIT is time varying as idiosyncratic volatility which increases dramatically during bad market times but declining marginally during good market times. Another interesting finding is that when idiosyncratic volatility is controlled for the regression model, size factor and the BE/ME factor become statistically insignificant.

Previous studies also find that the behaviour of idiosyncratic volatility is asymmetric, for example Ooi et al. (2009) suggest that idiosyncratic volatility of US REIT stocks increases significantly during bad market times, but decreases slightly during good market times. Campbell et al. (2001) also suggest that idiosyncratic volatility is high during economy recessions in the US. Due to the different behaviour of idiosyncratic volatility during different market times, the pricing ability of idiosyncratic volatility may be affected. However, there is lack of studies examining the pricing ability of idiosyncratic volatility during good market times and bad market times.

Many previous studies report that idiosyncratic volatility plays a significant role in asset pricing. The implication of these results is that investors should take into account the level of idiosyncratic volatility they have assumed in addition to the market risk. If investors fail to consider the effects of idiosyncratic volatility when estimating the required rate of return or cost of capital, assets will be mispriced. Portfolio managers should also be careful when evaluating the performance of their portfolios against the benchmark portfolios, as they need to compare their portfolios' performance against benchmark portfolios with matching idiosyncratic volatility. Overall, whether idiosyncratic volatility is priced for risky asset returns is an important issue to be addressed both in theory and in practice.

2.4. RELATIONSHIP BETWEEN IDIOSYNCRATIC VOLATILITY AND STOCK FUNDAMENTALS

Previous studies in the area of idiosyncratic volatility have focused on the pricing of assets. The majority of studies find that idiosyncratic volatility is priced for returns of risky assets, therefore suggesting that idiosyncratic volatility is an important asset pricing factor, and highlighting the importance of investigating the factors that are important in explaining idiosyncratic volatility. There is lack of research in this area, and, in particular, there aren't any known studies that investigate the Australian equity market.

Specifically, the majority of studies in this area have been conducted using US and Japanese data. For example, Wei and Zhang (2004) find that ROE is negatively related to idiosyncratic volatility and variance of ROE is positively related to idiosyncratic volatility in the US from 1976 to 2000. They suggest that the increase in idiosyncratic volatility over time is led by high idiosyncratic volatilities of newly listed companies as newly listed companies tend to have lower profitability. Brown and Kapadia (2005) find that an increase in idiosyncratic volatility in the US market is driven by new listings of riskier companies. They find newly listed companies are smaller in size, have lower profitability, are not likely to pay dividends, have more fractions of intangible assets and are highly likely to be 'growth' stocks. Chang and Dong (2006), using Japanese data, find the absolute firm earnings (measured by ROA and ROE) are positively related to idiosyncratic volatility from 1975 to 2003.

Previous studies in the area have found that factors that contain firm specific information, such as firm size and firm profitability ratios, explain idiosyncratic volatility.

Size is found to be negatively correlated to idiosyncratic volatility. Many previous studies provide evidence to support the negative correlation between the two variables. For example, Bali et al. (2005) find that small stocks tend to have high idiosyncratic volatility in the US. Chang and Dong (2006) use lagged firm size as a control variable in the regression function. They find lagged size is negatively related to the idiosyncratic volatility for the Japanese stock market. This negative relationship between the idiosyncratic volatility and size is not surprising since negative correlation between the two variables has been found in previous studies.

Profitability ratios, such as ROA and ROE, are found to explain idiosyncratic volatility. ROA and ROE are two of the most popular profitability ratios used by investors in determining stock prices. Hence, the roles of these ratios in determining stock prices cannot be ignored. Idiosyncratic volatility is calculated by using stock prices, so there are possible relationships between profitability ratios and idiosyncratic volatility.

Previous studies find evidence that support the relationship between idiosyncratic volatility and profitability ratios. Wei and Zhang (2004) find a negative relationship between ROE and the stock return volatility in the US from 1976 to 2000. Chang and Dong (2006) find ROA[4] is positively related to the idiosyncratic volatility using Japanese data. Even in the presence of control variables (lagged idiosyncratic volatility, lagged size and lagged return), the coefficient of ROA remains significant. They repeat the regressions by using ROE instead of ROA and the same results are obtained, hence suggesting that ROA and ROE play very similar roles in explaining idiosyncratic volatility.

[4] They define Return On Asset as the absolute value of the deviation of ROA from cross-sectional mean of ROA.

2.5. THE PREDICTABILITY OF ASSET PRICING FACTORS FOR THE GROWTH OF THE ECONOMY

Economic theory suggests that stock returns based on factors are leading indicators of economic activity. Previous studies provide substantial evidence to support the notion that stock returns predict economic activities. Fama (1981) finds that US stock returns lead growth rates of GNP and other real variables including capital expenditures, the real rate of return on capital and output. He suggests that stock market expectations provide rational forecasts to the economic activities. Moore (1983) finds that stock prices are leading indicators for business cycles for the period 1973 to 1975. Fischer and Merton (1984) confirm Moore's (1983) finding and suggest that the stock prices predict business cycles and the GNP during the period 1950 to 1982. They also find that stock prices lead the growth of investment and consumption. Barro (1990) finds that lagged changes of US stock prices predict the growth rate of investment activity during the period 1891 to 1987. Barro (1990) also documents similar findings for Canada. This study further linked stock market information and macroeconomic activities. He provides evidence to suggest that stock market information is a rational forecaster of macroeconomic activity. More recently, Estrella and Mishkin (1998) find that stock prices predict US recessions within three quarter horizons during the period 1959 to 1995. Their finding further confirms that the stock prices contain information in relation to the future macroeconomic activities.

The relationship between stock market information and economic activity has been studied internationally. For example, Aylward and Glen (2000) extend their study to 23 countries including Australia. They find stock prices are leading indicators for investment, GNP and consumption for various countries over the period 1951 to 1993, but the predictive power of the stock prices changes across countries in the sample. Hassapis and Kalyvitis (2002) investigate the link between real stock price changes and economic growth for G-7 countries. They find that stock price changes are related to the growth rate of GDP. The predictive power of stock market information is further confirmed in Europe. Panopoulou (2007) examines the predictive power of stock market returns to the growth of 12 countries from the Euro area and finds that stock market returns are the single most powerful predictors of growth in the 12 countries when compared to short-term interest rates, interest rate spreads and the future economic expectations. More recently, the predictive power of the stock market information to macroeconomic activities is examined in Asia-Pacific countries. For example, Ibrahim (2010) examines the predicative power of stock market returns to the growth rate of GDP in Malaysia. Ibrahim (2010) provided evidence to show that stock market returns predict real output at short horizons, specifically less than 4-quarter horizons for the period 1978 to 2008.

Despite the fact that a substantial number of empirical studies support that stock market information predicts macroeconomic activities, a few contrary findings have been reported in the literature. Stock and Watson (1990) find that the predictive power of stock returns to economic growth is not stable over time in the US for the period 1959 to 1988. Binswanger (2000) provides evidence to show that the predictive power of the stock returns to subsequent economic activities disappeared in the US in early 1980's. Binswanger (2001) find similar results for Japan.

Various studies conclude that the stock market contains information about future economic activity. A link between the Fama and French three-factor and the growth rate of the economy is established by Liew and Vassalou (2000). As the Fama and French three-factor model is one of the most important developments in the area of asset pricing, Liew and Vassalou (2000) find that Fama and French three factors predict future growth rates of GDP in the developed countries including Australia. They provide motivation to further explore the relationship between these risk mimicking asset pricing factors and the growth rates of macroeconomic indicators.

Recent studies show that there is a significant relationship between idiosyncratic volatility and stock returns. For example, Ang et al. (2006) find a negative relationship between lagged idiosyncratic volatility and future stock returns in the US. Ang et al. (2009) find a negative relationship between lagged idiosyncratic volatility and future stock returns in 22 developed countries. Their empirical results support the assumption that investors hold under-diversified portfolios hence idiosyncratic volatility is priced for the portfolios returns. Fu (2009) find a positive relationship between idiosyncratic volatility and stock returns in the US and support that idiosyncratic volatility is a significant asset pricing factor in addition to the Fama and French three-factor. More recently, Nartea, Ward and Yao (2011) find a positive relationship between idiosyncratic volatility and stock returns in Southeast Asian stock markets including Malaysia, Singapore, Thailand and Indonesia. Their finding suggests that the explanatory power of idiosyncratic volatility to stock returns is not country specific. These recent studies suggest that idiosyncratic volatility is a significant asset pricing factor even in presence of the Fama and French three-factor. As a significant asset pricing factor which contains stock market information, idiosyncratic volatility may contain different information in regard to macro economy other that the information contained in Fama-French three-factor.

2.6. CHAPTER SUMMARY

This chapter has summarized some of the most relevant literature in the areas of idiosyncratic volatility and asset pricing, and outlines the motivation for the research undertaken in this thesis. The majority of studies undertaken in these areas have been conducted using US data. Interestingly, important issues such as the relationship between idiosyncratic volatility and risky asset returns, the factors that explain idiosyncratic volatility and the information content of idiosyncratic volatility have not been adequately addressed to date. In addition, there is lack of research in these areas using Australian data. Hence, this thesis addresses these important issues by using analysing the Australian equity market and attempts to fill the gaps in understanding the effects of idiosyncratic volatility in Australia stock returns.

CHAPTER 3

3. THE PRICING OF IDIOSYNCRATIC VOLATILITY ON STOCK RETURNS

3.1. INTRODUCTION

CAPM of Sharpe (1964) and Lintner (1965) models returns using systematic risk, implying idiosyncratic volatility has no role in explaining asset returns. The underlying theory of CAPM is that idiosyncratic volatility is diversified away since investors hold a proportion of the well-diversified market portfolio. In reality, however, this is not always the case. Several studies have identified that for various reasons, investors do not always hold well-diversified portfolios (see example Malkiel and Xu, 2006; Goetzmann and Kumar, 2004), and therefore systematic risk is not necessarily the only risk factor to be priced.

Merton (1987) suggests that investors are compensated for holding underdiversified portfolios. The question of whether idiosyncratic volatility is priced has therefore attracted increasing attention amongst researchers in this area. Interestingly, studies to date have been inconclusive. For example, Malkiel and Xu (1997, 2006), Goyal and Santa-Clara (2003) and Fu (2009) find that idiosyncratic volatility is significantly and positively related to US stock returns, whereas Ang, Hodrick, Xing and Zhang (2006) find a negative relationship between lagged idiosyncratic volatility and future average returns in the US. In a follow up investigation, Ang, Hodrick, Xing and Zhang (2009) also report a negative relationship between lagged idiosyncratic volatility and future average returns in the seven largest equity markets in the world. Interestingly, although the reported results are mixed, most support the notion that idiosyncratic volatility is an omitted pricing factor by CAPM.

In this chapter, the role of idiosyncratic volatility in pricing of Australian stocks is explored. Following Fama and French (1993), an idiosyncratic volatility mimicking factor is constructed to mimic the risk in relation to idiosyncratic volatility. The primary objective is to test whether this idiosyncratic volatility factor is priced for returns of Australian stocks. Both the time-series relationship and the cross-sectional relationship between the idiosyncratic volatility factor and stock returns are investigated in this chapter. Further, the pricing ability of the idiosyncratic volatility factor is examined in both economic expansions and contractions.

Recent studies in the area of idiosyncratic volatility have focused on its asset pricing role. As idiosyncratic volatility is not directly obtainable, different measurements of idiosyncratic volatility have been developed and employed in different studies in order to explore and understand the full potential of the asset pricing role of idiosyncratic volatility. For example, Ang et al. (2006, 2009) use lagged realized idiosyncratic volatility as an explanatory variable, while Fu (2009) uses expected idiosyncratic volatility as an explanatory variable. In this Chapter, a new measurement of idiosyncratic volatility is developed and the asset pricing role of idiosyncratic volatility is explored. This new measurement of idiosyncratic volatility is inspired by Fama and French (1993) as their study finds that portfolios constructed to mimic common risk factors, such as size and BE/ME, explain significant variations in US stock returns which indicates that risk mimicking factors also play an important role in explaining variations in stock returns. Therefore, this new measurement is developed based on Fama and French's risk mimicking portfolio approach by constructing an idiosyncratic volatility mimicking portfolio.

In this Chapter, the asset pricing role of idiosyncratic volatility is investigated by using Australian data. There are several reasons to support the use of Australian data. First, much of the research in this area concentrates on US stock returns. According to the MSCI global index ranking, the Australian stock market was ranked the eighth largest stock market in the world by market capitalisation as at 31 August 2012.[5] Therefore, a major contribution of this chapter is that it provides insights into one of the most important financial markets globally that has not, to date, been investigated in a significant way. Second, there are small numbers of large stocks by size listed on the Australian stock market, but these stocks are very large by market capitalization and they contribute a significant proportion to total market capitalization of the Australian stock market. For example, the top 100 largest companies listed on the Australian Securities Exchange made up approximately 74% of the Australian stock market by market capitalization[6] by the end of 2011. Bali et al. (2005) suggest that the effect of idiosyncratic volatility is more pronounced with small stocks. However, as there is lack of Australian studies in this area, it is not known if idiosyncratic volatility is priced in the Australian stock market nor is the effect of idiosyncratic volatility on small and large Australian companies. Third, the pricing ability of the idiosyncratic volatility factor is tested during economic expansions and contractions. The primary objective of this analysis is to examine whether this idiosyncratic

[5] http://www.asxgroup.com.au/the-australian-market.htm
[6] http://www.spindices.com/indices/equity/sp-asx-100

volatility mimicking factor is an omitted explanatory variable for the existing asset pricing models in explaining Australian stock returns.

This Chapter contributes to the literature in several ways. Following Fama and French (1993) and Drew, Naughton and Veeraraghavan (2004) to construct a HIMLI factor by using the returns of high idiosyncratic volatility portfolios minus the returns of low idiosyncratic volatility portfolios. However, unlike Drew et al. (2004) who define the idiosyncratic volatility as the difference between total risk and the systematic risk of a stock, idiosyncratic volatility is defined as the standard deviation of the regression residual of the Fama and French three-factor model in this chapter. This definition has been implemented in several leading studies in the area, including Ang et al. (2006, 2009) and Fu (2009).

Then following Fama and French (1993), 25 size and BE/ME sorted portfolios are constructed and the explanatory power of the idiosyncratic volatility factor is examined by using a four-factor model. This four-factor model consists of Fama and French three-factor and an idiosyncratic volatility factor. Further, the cross-sectional relationship between our HIMLI factor and Australian stock returns is examined by using Fama and Macbeth (1973) regressions. In addition, the stability of the idiosyncratic volatility factor in pricing stock returns is investigated during different phases of business cycles. This is motivated by a number of relevant studies in the literature. For example, Campbell et al. (1997) report that idiosyncratic volatility increases during economic downturns, thus suggesting that the pricing ability of idiosyncratic volatility may not be stable. Lettau and Ludvigson (2001) find that stock returns vary in the different phases of business cycles and therefore argue that the pricing ability of idiosyncratic volatility factor may be affected. Ooi et al. (2009) also report that idiosyncratic volatility increases significantly during bad market cycles but decreases slightly during good market times. Therefore, this study is motivated to explore the pricing ability of idiosyncratic volatility in different phases of the business cycle.

The empirical results reveal numerous interesting findings. The results show that high idiosyncratic volatility stocks are small stocks with high returns. This finding is consistent with Bali et al. (2005) who find small stocks have high idiosyncratic volatility in the US. The time series analysis reveals that the idiosyncratic volatility factor is priced for the returns of Australian stocks from January 2002 to December 2010 on the size and BE/ME portfolios. Specifically a significant positive relationship between the idiosyncratic volatility factor and stock returns is shown to exist. Importantly, the idiosyncratic volatility factor captures greater variations in return of small and high idiosyncratic volatility stocks than large and low idiosyncratic volatility stocks. This finding suggests that the idiosyncratic volatility factor augmenting Fama and French three-factor model captures more information contained in small stocks. This evidence supports that idiosyncratic volatility is more strongly associated with small stocks and the effect of idiosyncratic volatility is more pronounced in the pricing of small stocks. This finding is consistent with Guo and Savickas (2010) who find that the IVF factor is a significant pricing factor in cross-sectional US stock returns from 1994 to 2005. They define IVF as the return difference between low and high CAPM based idiosyncratic volatility. They suggest that the explanatory power of IVF should be much weaker for low idiosyncratic volatility portfolios as high idiosyncratic volatility stocks are more sensitive to discount rate shocks than low idiosyncratic volatility stocks. The pricing of HIMLI factor is also consistent with Bali et al. (2005). They find that the positive relationship between idiosyncratic volatility and stocks return is driven by small stocks listed on the NASDAQ. The idiosyncratic volatility factor is also priced for the ten idiosyncratic volatility sorted portfolios from 1993 to 2000 and it is pricing in both economy expansions and contractions. Moreover, the results show that the model captures greater variation of the stock returns during expansion than contractions.

The empirical findings can be explained by the characteristic of the Australian stock market. According to the S&P INDICES, the 20 largest stocks by market capitalization made up approximately 46% of the stock market at the end of 2010[7]. Therefore, it is not surprising that the idiosyncratic volatility factor captures additional variations in Australian stock returns which are omitted by the Fama and French three-factor model due to the fact that Australian stock market consists of fewer big stocks and a larger number of smaller stocks. Hence, the effect of idiosyncratic volatility is significant for the pricing of Australian stocks. Further, the empirical results show a significant and robust positive cross-sectional relationship between the Australian stock returns and the idiosyncratic volatility factor. The empirical results provide consistent and strong evidence to support the idiosyncratic volatility factor is an omitted pricing factor in the asset pricing models for pricing of Australian stocks.

The empirical findings have some practical implications for the investors. The results indicate that idiosyncratic volatility should not be ignored when estimating the required rate of return and the cost of capital. Moreover, investors should match the idiosyncratic volatility of their portfolios with the benchmark portfolio when evaluating the performance of the portfolios.

[7] http://www.spindices.com/indices/equity/sp-asx-20

The remainder of this chapter is organized as follows. First, Section 3.2 describes the data and summary statistics. Section 3.3 outlines the methods employed in this study. Section 3.4 presents the empirical results. Finally, Section 3.5 provides the concluding comments.

3.2. DATA

Australian stock return data are obtained from Datastream for the period of January 1993 to December 2010. The 90-day Australian Bank Accepted Bill Rate is obtained from the Reserve Bank of Australia website to represent a proxy for the risk free rate in Australia. Total return indices of the stocks are used to calculate the average returns of the stocks. ASX All Ordinaries Total Return Index is used to calculate the average return of the market proxy. The total return index is the accumulation return index adjusted for dividends and other capital issues. Monthly market capitalization data is used to represent the size of stocks, and monthly market to book values are used to calculate the relevant BE/ME ratios. The initial sample included all active and dead companies listed on Australian Securities Exchange during the sample period.

Guant (2004) suggests that a large number of thinly traded stocks in the sample reduce the statistical reliability of the portfolios returns as thinly traded and delisted stocks may show constant returns in post portfolios formation periods. In order to avoid thin trading effect, the following two filters are applied to obtain the final sample:

1. Following Guant (2004), only stocks that had at least one trade in a month were included to avoid any possible thin trading effects; and
2. Only stocks that had the following available data were included: daily and monthly total return, monthly market capitalization and monthly market to book value.
3. Statman (1987) suggests that a well-diversified portfolio must include at least 30 randomly selected stocks. Campbell et al. (2001) suggests that the number of stocks to achieve a given level of diversification increased from 1962 to 1997. Therefore, in order to maintain the level of diversification for the 25 size and BE/ME portfolios, it is required on average each portfolio must contain at least 40 stocks. Since there are less than 1000 stocks in our sample prior to 2002, the final sample period for the regressions based on the 25 size and BE/ME portfolio has been shortened to January 2002 to December 2010. However, for the regressions based on ten idiosyncratic volatility sorted portfolios the sample period is from January/1993 to December/2010.

Table 3.1 provides the number of stocks in the whole sample and their average returns, average size, average book-to-market equity ratio and average idiosyncratic volatility from 1993 to 2010. The smallest contribution of initial sample to the final sample is in 1993 (422 stocks), and the largest contribution is in 2008 (1773 stocks). It is evident that idiosyncratic volatility increases dramatically during bad market times but decreases marginally during good market times. For example, average idiosyncratic volatility increased from 1997 to 2001, a period that includes the Asian Financial Crisis, the dot.com bubble, and 911. Idiosyncratic volatility increased again from 2007 to 2008, and this period includes the most volatile periods for the stock market, namely the sub-prime mortgage crisis and the GFC. The behaviour of idiosyncratic volatility in Australia is consistent with that reported by Campbell et al. (2001) and Ooi et al. (2009).

Table 3.1 Yearly summary statistics over the sample period

Year	Number of Stocks	Return	Size	BE/ME	Idiovol
1993	422	0.0628	474	0.8564	0.1620
1994	480	0.0152	524	0.6741	0.1540
1995	529	0.0261	490	0.7701	0.1463
1996	737	0.0351	415	0.7110	0.1606
1997	822	-0.0087	435	0.7763	0.1712
1998	862	0.0029	514	0.9112	0.1954
1999	888	0.0480	637	0.8776	0.1983
2000	980	0.0182	655	0.7970	0.2106
2001	1083	-0.0003	619	1.0780	0.2162
2002	1111	0.0035	603	1.0110	0.2032
2003	1141	0.0433	573	0.9398	0.1972
2004	1255	0.0227	634	0.7465	0.1638
2005	1380	0.0065	716	0.7481	0.1705
2006	1485	0.0313	797	0.7193	0.1839
2007	1612	0.0237	912	0.6014	0.1860
2008	1773	-0.0649	723	0.8178	0.2591
2009	1771	0.0736	617	1.2262	0.2556
2010	1746	0.0179	765	0.8234	0.1989

Note. This table shows the average number of stocks, average monthly return, average size (in millions) of the companies, average monthly BE/ME, and average monthly idiosyncratic volatility (Idiovol) from 1993 to 2010 on annual basis.

Table 3.2 presents the descriptive statistics of the relevant variables used in the regression equations. It is observed that (i) the average market return is 0.77% per month from January 2002 to December 2010, (ii) the monthly average excess return of the market portfolio, average return of size mimicking portfolio, book-to-market equity ratio mimicking portfolio and idiosyncratic volatility mimicking portfolio are 0.33%, 1.76%, 2.6% and 1.74% respectively, and (iii) the return based factors, such as the market factor (RMRF), the size factor (SMB), the BE/ME factor (HML) and the idiosyncratic volatility factor (HIMLI), are close to normal distribution.

Table 3.2 Descriptive summary statistics of the variables

Variables	Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis
Market Returns	0.0077	0.0194	0.1096	-0.1324	0.0433	-0.7672	3.8036
Ln(SIZE)	6.5439	6.5715	6.8851	6.1541	0.1662	-0.0421	2.2343
BE/ME	0.8482	0.7861	1.6546	0.5295	0.2212	1.4373	5.2350
Idiovol	0.2020	0.1940	0.3664	0.1429	0.0395	1.4975	5.6121
RMRF	0.0033	0.0145	0.1069	-0.1366	0.0434	-0.7506	3.8055
SMB	0.0176	0.0146	0.1462	-0.0438	0.0347	0.8951	4.2870
HML	0.0260	0.0237	0.0926	-0.0359	0.0257	0.4790	3.2431
HIMLI	0.0174	0.0155	0.1689	-0.0844	0.0541	0.3312	2.7545

Note. This table shows the descriptive summary statistics of the relevant variables including Market Return, Ln(SIZE), BE/ME, idiosyncratic volatility (Idiovol), excess market return (RMRF), Fama and French size factor (SMB) and BE/ME factor (HML) and the idiosyncratic volatility mimicking factor (HIMLI) from 2002 to 2010.

3.3. METHODOLOGY

In this section, the methodology of this study is outlined. The main steps can be summarized as: (1) idiosyncratic volatility is measured by using regression residual from a three-factor model, (2) the idiosyncratic volatility factor, a size factor and a BE/ME factor are constructed, (3) 10 idiosyncratic volatility sorted stock portfolios and 25 size and BE/ME sorted stock portfolios are constructed, and (4) the idiosyncratic volatility factor is tested in the pricing the returns of ten idiosyncratic volatility sorted stock portfolios and 25 size and BE/ME sorted stock portfolios.

3.3.1. CONSTRUCTION OF FAMA AND FRENCH RISK MIMICKING FACTORS BY USING DAILY STOCK RETURNS AND ESTIMATION OF THE IDIOSYNCRATIC VOLATILITY

Idiosyncratic volatility is not directly observable. In this Chapter, idiosyncratic volatility is defined as the monthly standard deviation of the regression residual from the Fama and French three-factor model (see Equation 1), so the first step for estimating idiosyncratic volatility is to construct the size factor (hereafter SMB) and the BE/ME factor (HML) by using daily stock returns. The SMB and HML factors/portfolios are constructed as follows: Companies are divided into two size portfolios and three book-to-market equity ratio portfolios. The two size portfolios consist of (i) the top 50% of companies (big) by market capitalization, and (ii) the bottom 50% companies (small) by market capitalization. The three book-to-market equity ratio portfolios consist of (i) 1/3 high book-to-market equity ratio companies, (ii) 1/3 medium book-to-market equity ratio companies, and (iii) 1/3 low book-to-market equity ratio companies. Every year t, the companies are ranked and sorted into portfolios according to their size and book-to-market equity ratio at December of year t-1. The daily SMB factor is calculated as the daily returns of the big size portfolio minus the daily returns of the small size portfolio. Daily HML factor is calculated as the daily returns of the high book-to-market equity ratio portfolio minus the daily returns of the low book-to-market equity ratio portfolio. The portfolios are rebalanced on an annual basis.

Following Ang et al. (2006, 2009), idiosyncratic volatility is defined as the standard deviation of regression residuals of the Fama and French (1993) three-factor model.

Over the sample period, daily excess returns of stock i are regressed on the daily market factor, daily size factor and daily BE/ME factor. The regression equation is the following:

$$r_{it} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + \varepsilon_{it} \qquad (3.1)$$

Where r_{it} is the daily returns of stock i, r_{ft} is the daily 90-day bank acceptable bill rate, r_{mt} is the daily returns of S&P/ASX All Ordinary Index, SMB and HML are the daily returns of risk factor mimicking portfolios for size and book-to-market ratio respectively. Idiosyncratic volatility is estimated as the standard deviation of regression residual ε_{it} after regressing equation (1). Subsequently the standard deviation of daily regression residuals is transformed to a monthly value by multiplying the square root of the number of trading days in the month.

3.3.2. CONSTRUCTION OF FAMA AND FRENCH RISK MIMICKING FACTORS AND THE IDIOSYNCRATIC VOLATILITY MIMICKING FACTOR BY USING MONTHLY STOCK RETURNS

Following the same procedure outlined in Section 3.3.1., the monthly size factor and monthly BE/ME factor are constructed by using monthly stock returns.

As monthly idiosyncratic volatility is estimated for every stock in the sample, the next step is to construct the idiosyncratic volatility factor. Following the risk mimicking portfolio approach of Fama and French (1993), the idiosyncratic volatility mimicking portfolio HIMLI (also called the idiosyncratic volatility factor) is constructed to mimic the risk in relation to idiosyncratic volatility by using the following method: stocks are sorted into three idiosyncratic volatility portfolios consisting of 1/3 high idiosyncratic volatility companies, 1/3 medium idiosyncratic volatility companies and 1/3 low idiosyncratic volatility companies. Every year t, the companies are ranked and sorted into portfolios according to their idiosyncratic volatility at December of year t-1. The monthly HIMLI factor is calculated as the return of high idiosyncratic volatility portfolio minus return of low idiosyncratic volatility portfolio. As with SMB and HML portfolios, the HIMLI portfolio is rebalanced on an annual basis.

3.3.3. TIME SERIES REGRESSION ANALYSIS

The following regression equation is used to examine the pricing of HIMLI factor:

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + iHIMLI_t + \varepsilon_t \qquad (3.2)$$

Where r_t is the monthly returns of portfolio i, r_{ft} is the monthly 90-day bank acceptable bill rate, r_{mt} is the monthly return of S&P/ASX All Ordinary Index, *SMB* and *HML* are Fama and French risk factor mimicking portfolios for size and book-to-market ratio and *HIMLI* is the monthly returns of the idiosyncratic volatility factor.

3.3.4. CONSTRUCTION OF TEN IDIOSYNCRATIC VOLATILITY PORTFOLIOS

Once the idiosyncratic volatility factor is constructed, the next step is to construct ten idiosyncratic volatility sorted stock portfolios. The purpose is to reveal the characteristics of the idiosyncratic volatility sorted portfolios in regard to return, risk, size and BE/ME. In Section 3.4, this study further examines whether the idiosyncratic volatility factor explains the returns of ten idiosyncratic volatility sorted portfolios.

On January of each year t, ten portfolios of stocks are constructed according to idiosyncratic volatility at December of the previous year with each portfolio comprising of an equal number of stocks. The portfolios are held for one year, and rebalanced in January of the following year. The sample period for the regressions based on these ten idiosyncratic volatility sorted portfolios is extended to January 1993 to December 2010 as there are sufficient stocks in each portfolio since the beginning of the sample period. This provides a time series of monthly returns on each portfolio from 1993 to 2010. Pricing of the idiosyncratic volatility factor is further examined by using the ten idiosyncratic volatility sorted portfolios.

Table 3.3 Summary statistics of ten idiosyncratic volatility sorted portfolios

Portfolio	Monthly Excess Return	Std Dev	Size (millions)	BE/ME
1(high)	4.16%	11.67%	21	0.5994
2	1.81%	9.57%	38	0.5767
3	1.57%	8.71%	59	0.6433
4	1.07%	7.79%	68	0.5977
5	0.95%	6.62%	176	0.6497
6	0.62%	5.81%	334	0.6638
7	0.67%	5.02%	970	0.6467
8	0.72%	4.43%	1327	0.6818
9	0.96%	3.98%	2215	0.6628
10(low)	1.51%	5.55%	1249	0.5376

Note. This table shows summary statistics of ten idiosyncratic volatility sorted portfolios. All Australian stocks are equally sorted into ten portfolios according to their idiosyncratic volatilities. Portfolios 1 consists of highest idiosyncratic volatility stocks and portfolios 10 consists of lowest idiosyncratic volatility stocks.

Table 3.3 reports the summary statistics of ten idiosyncratic volatility sorted portfolios. The monthly stock returns are ranked by idiosyncratic volatility in the previous December and sorted into ten idiosyncratic volatility ranked portfolios with an equal number of stocks in each portfolio. These portfolios are held for one year and rebalanced in the following year. Portfolio 1 comprises the stocks with highest idiosyncratic volatility and portfolio 10 comprises the stocks with lowest idiosyncratic volatility. Table 3.3 reports the summary statistics of ten idiosyncratic volatility portfolios. Overall, the average size is noted to increase when moving from the high idiosyncratic volatility portfolio (portfolio 1) to the low idiosyncratic volatility portfolio (portfolio 9) but decreases when moving from portfolio 9 to 10. Generally speaking, high idiosyncratic volatility stocks are small stocks. This finding is consistent with that reported by Bali et al. (2005) who suggest that small companies have high idiosyncratic volatility. There is no such pattern in the BE/ME variable when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio.

Table 3.3 suggests that high idiosyncratic volatility stocks are small stocks. Hence, the idiosyncratic volatility factor is expected to be positively correlated to the size factor. To gain a greater insight into the relationship between these explanatory variables, the correlation coefficients are presented in Table 3.4. The correlation between SMB and HIMLI is significantly at 67%. The correlation between these two explanatory variables indicates a close but not exact relationship which may suggest that the t-statistics are unreliable. In order to confirm whether or not multicollinearity is a concern in this study, the Variance Inflation Factor (VIF) is calculated for the explanatory variables. These values are all less than 5, thus indicating that multicollinearity is not an issue.

Table 3.4 Correlation coefficients between the independent variables

correlation coefficients			
	RMRF	**SMB**	**HML**
SMB	0.0287		
t-stat	0.42		
HML	-0.1801**	0.0798	
t-stat	-2.68	1.17	
HIMLI	0.3258***	0.6688***	-0.1180
t-stat	5.04	13.16	-1.74

Note. The degree of multicollinearity is analysed by calculating the Variance Inflation Factor (VIF). The values of VIF are less than 4.78 which suggest that multicollinearity is not an issue in this study.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

3.3.5. CONSTRUCTION OF 25 FAMA AND FRENCH SIZE AND BE/ME PORTFOLIOS

The idiosyncratic volatility factor is further examined in explaining the returns of 25 size and BE/ME stock portfolios in presence of Fama and French's three factors. In order to construct 25 size and BE/ME sorted portfolios, the monthly stock returns are ranked by size and BE/ME in the previous December and sorted into 25 portfolios. These portfolios are held for one year and rebalanced in the following year. Portfolio 11[8] comprises the stocks with biggest size and highest BE/ME stocks, while portfolio 55[9] comprises smallest size and lowest BE/ME stocks. Both equally weighted stock portfolios and value weighted stock portfolios are constructed.

The purpose of this approach is to exam the power of the idiosyncratic volatility factor in explaining both equally weighted and value weighted returns of the 25 size and BE/ME portfolios. The sample period is from January 2002 to December 2010. It is expected that the idiosyncratic volatility factor explains more variation in the returns of equally weighted portfolios than value weighted portfolios as Bali et al. (2005) suggest the effect of idiosyncratic volatility is more pronounced with small stocks.

3.3.6. FAMA-MacBETH (1973) CROSS-SECTIONAL REGRESSIONS

After the time-series relationship between the idiosyncratic volatility factor and stock returns is examined, this chapter further examines the cross-sectional relationships by implementing Fama and Macbeth (1973) cross-sectional regressions.

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[8] Portfolio 11 represents the 1st portfolio.
[9] Portfolio 55 represents the 25th portfolio.

The Fama and Macbeth (1973) approach is summarized as follows:

(1) The coefficients of the market factor, SMB, HML and HIMLI for all companies in the final sample are calculated by estimating the following model:

$$r_{it} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + iHIMLI_t + \varepsilon_{it} \tag{3.3}$$

where r_{it} is the monthly returns of stock i, r_{ft} is the monthly 90-day bank acceptable bill rate, r_{mt} is the monthly return of S&P/ASX All Ordinary Index, *SMB* and *HML* are Fama and French risk factor mimicking portfolios for size and book-to-market ratio and *HIMLI* is the monthly returns of the idiosyncratic volatility factor.

(2) The relationship between the average excess returns of the stocks and the coefficients of the market factor, SMB, HML and/or HIMLI are estimated by using the following models:

$$\overline{r_t - r_{ft}} = \alpha + \gamma_1\beta + \varepsilon_t \tag{3.4}$$

$$\overline{r_t - r_{ft}} = \alpha + \gamma_1\beta + \gamma_4 i + \varepsilon_t \tag{3.5}$$

$$\overline{r_t - r_{ft}} = \alpha + \gamma_1\beta + \gamma_2 s + \gamma_3 h + \gamma_4 i + \varepsilon_t \tag{3.6}$$

Where $\overline{r_t - r_{ft}}$ is the average of monthly excess returns of all stocks in the final sample, β is the coefficient of the market factor from equation (3.3), s is the coefficient of SMB from equation (3.3), h is the coefficient of HML from equation (3.3) and i is the coefficient of HIMLI from equation (3.3).

3.4. EMPIRICAL RESULTS

3.4.1. TIME SERIES REGRESSION RESULTS: PRICING IDIOSYNCRATIC VOLATILITY IN THE RETURNS OF 25 EQUAL-WEIGHTED PORTFOLIOS

Table 3.5 presents the regression results of the Fama and French three-factor model based on 25 equally-weighted size and BE/ME portfolios. The three factors capture strong time series variation in stock returns.

As expected, the coefficients of the market factor (hereafter RMRF) are all significant and positive which suggest RMRF explains strong variation in the excess returns of the 25 size and BE/ME portfolios. Generally, the coefficients of RMRF are related to size as the coefficients show decreasing patterns when moving from bigger stock portfolios to smaller stock portfolios. These decreasing patterns suggest that big size stocks are riskier than small size stocks in terms of systematic risk. It is an interesting finding as conventional wisdom suggests that big size stocks are less risky than small size stocks so that big size stocks should have smaller coefficients than small size stocks. This finding is futher discussed in section 3.4.3.

The size factor or SMB is found to be an important determinant of stock returns as 23 out of 25 coefficients are significant. The coefficients increase when moving from bigger size stock portfolios to smaller size stock portfolios. There are no patterns in the coefficients of SMB when moving across BE/ME stock quintiles.

The coefficients of BE/ME factor or HML are related to BE/ME as the highest BE/ME quintile shows positive coefficients and the lowest BE/ME quintile shows negative coefficients. Sixteen out of 25 coefficients of HML are significant, 10 out of these 16 significant coefficients are from highest and lowest BE/ME quintiles. Adjusted R-squared values are high with 18 out of 25 values being greater than 70%. The lowest adjusted R-squared value is 61.79% and the highest is 86.58%. These results suggest that a significant proportion of variations in the returns is captured by the three-factor model.

Table 3.5 Fama and French three-factor model: 25 equal-weighted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + \varepsilon_t$$

	BE/ME										
Size	**1 (High)**	**2**	**3**	**4**	**5 (Low)**		**1 (High)**	**2**	**3**	**4**	**5 (Low)**
			Alpha						**RMRF**		
1 (Big)	-0.0125*	-0.0055***	-0.0044	0.0022	-0.0022		1.4584***	1.1085***	1.0978***	1.1263***	1.1396***
t-stat	-1.68	-1.74	-1.58	0.80	-0.67		12.34	22.19	25.01	25.33	21.67
2	-0.0111*	-0.0086**	-0.006	-0.0094**	-0.0183***		1.0824***	1.0237***	0.9231***	1.0441***	1.0854***
t-stat	-2.27	-2.23	-1.44	-2.27	-4.01		13.96	16.76	13.95	15.91	15.02
3	-0.0015	-0.006	-0.0083	-0.0128**	-0.0260***		0.9270***	0.8945***	1.0184***	1.0213***	0.9653***
t-stat	-0.28	-1.28	-1.57	-2.40	-5.09		11.44	12.05	12.27	12.11	11.95
4	-0.0033	-0.0081	-0.0140***	-0.0166***	-0.0259***		0.8871***	0.8920***	1.0622***	0.9762***	0.8660***
t-stat	-0.54	-1.53	-2.50	-2.86	-4.97		9.34	10.62	11.99	10.63	10.52
5 (Small)	-0.0053	0.0018	-0.0002	0.0116	0.0049		0.8178***	0.7676***	0.9010***	0.8815***	0.7767***
t-stat	-1.03	0.26	-0.03	1.24	0.70		10.07	6.79	7.70	5.97	6.99
			SMB						**HML**		
1 (Big)	0.1565	0.0037	0.0965*	0.1209**	0.2303***		0.7938***	0.2225***	0.1442*	-0.0393	-0.2319***
t-stat	1.06	0.06	1.76	2.17	3.50		4.04	2.68	1.98	-0.53	-2.65
2	0.4623***	0.3953***	0.5795***	0.6955***	0.6952***		0.4837***	0.1408	0.0095	-0.1351	-0.4137***
t-stat	4.76	5.17	7.00	8.47	7.69		3.75	1.39	0.09	-1.24	-3.45
3	0.7630***	0.8079***	1.1364***	1.0889***	1.1280***		0.2456*	0.1096	-0.3292**	-0.4938***	-0.5931***
t-stat	7.52	8.70	10.94	10.32	11.16		1.82	0.89	-2.39	-3.52	-4.42
4	1.0874***	1.3991***	1.4603***	1.5767***	1.5539***		0.4700**	-0.0948	-0.1876	-0.3139**	-0.6265***
t-stat	9.15	13.31	13.17	13.72	15.08		2.98	-0.68	-1.27	-2.06	-4.58
5 (Small)	1.6258***	1.8036***	1.6417***	1.9709***	1.5520***		1.0646***	0.2465	-0.1243	-0.6405**	-0.4413**
t-stat	15.99	12.74	11.20	10.67	11.16		7.89	1.31	-0.64	-2.61	-2.39
			R^2						**BIC**		
1 (Big)	61.79%	82.66%	86.14%	86.58%	83.40%		-2.94	-4.66	-4.92	-4.89	-4.56
2	70.77%	76.57%	72.81%	78.35%	76.57%		-3.78	-4.26	-4.10	-4.11	-3.92
3	67.96%	71.35%	75.69%	74.87%	76.23%		-3.69	-3.87	-3.64	-3.61	-3.70
4	66.94%	76.67%	78.33%	77.45%	79.88%		-3.38	-3.62	-3.51	-3.54	-3.66
5 (Small)	82.39%	69.96%	67.41%	62.86%	66.30%		-3.69	-3.03	-2.96	-2.49	-3.06

Note. This table reports the pricing of the market factor, the size factor and the book-to-market equity factor in 25 Fama and French size and BE/ME portfolios.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3.6 presents the regression results of a four factor model based on 25 equally-weighted size and BE/ME portfolios. It's not surprising that RMRF explains variations in the excess returns of the portfolios. All of the market factor coefficients are significant at the 1% level. Consistent with the results in Table 3.5, the coefficients of RMRF decrease when moving from bigger size stocks to smaller size stocks. Fourteen of the 25 coefficients of SMB are significant in this table compared to 23 out of 25 significant coefficients in Table 3.5. These significant coefficients show an increasing pattern when moving from the big stock portfolio (portfolio 3) to the small stock portfolio (portfolio 5). This is consistent with the findings of Fama and French (1993) who report that small stock portfolios have bigger loadings for the size factor.

Turning our attention to HML factor, 17 out of 25 coefficients are significant compared to 16 out 25 significant coefficients of HML factor in Table 3.5. The coefficients of HML are related to the BE/ME as the highest BE/ME quintile shows positive coefficients and the lowest BE/ME quintile shows negative coefficients. This is consistent with the results of Fama and French (1993). Interestingly, 19 out of 25 coefficients of HIMLI factor are significant and positive, which suggests that HIMLI explains variation in the excess returns of the size and BE/ME sorted portfolios. Generally, there are increasing patterns in the coefficients for HIMLI when moving from bigger stock quintiles to smaller stock quintiles for second and fourth BE/ME stock quintiles. Another interesting finding is that 9 coefficients of SMB become insignificant and the values of significant coefficients become smaller once HIMLI is added to the regression equation. This result suggests that HIMLI captures information that is missed by the Fama and French three-factor model as well as similar information that captured by the SMB factor. The adjusted R-squared values for the regressions are relatively higher with the lowest value of 62.95% and the highest value of 87.07% compared to those of Table 3.5. The adjusted R-squared improves by approximately 3% for the second to fourth size quintiles after HIMLI is added to the three-factor model which suggests our four-factor model captures more variation in the stock returns than the three-factor model. The regression results in Table 3.6 show that the pricing of the HIMLI factor is robust in the 25 Fama and French size and BE/ME portfolios, and the HIMLI factor is positively related to the returns of Australian stocks over the sample period. The implication of this finding is that idiosyncratic volatility is important in the pricing of Australian stock returns, so it should not be omitted in the asset pricing model. In practice, idiosyncratic volatility should not be ignored when estimating the required rate of return of Australian stocks and evaluating the performance of Australian stock portfolios.

Table 3.6 Fama and French three-factor model augmented by an idiosyncratic volatility factor: 25 equal-weight portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + iHIMLI_t + \varepsilon_t$$

	BE/ME										
Size	**1 (High)**	**2**	**3**	**4**	**5 (Low)**		**1 (High)**	**2**	**3**	**4**	**5 (Low)**
			Alpha						**RMRF**		
1 (Big)	-0.0128*	-0.0055*	-0.0045	0.0021	-0.0023		1.2632***	1.0856***	1.0477***	1.0470***	1.0374***
t-stat	-1.73	-1.74	-1.61	0.78	-0.72		8.43	16.82	18.62	18.63	15.68
2	-0.0114*	-0.0088**	-0.0062	-0.0096**	-0.0186***		0.9025***	0.8876***	0.7396***	0.8613***	0.8880***
t-stat	-2.40	-2.35	-1.57	-2.45	-4.28		9.37	11.66	9.16	10.77	10.06
3	-0.0018	-0.0062	-0.0085*	-0.0131**	-0.0261***		0.6874***	0.7312***	0.7858***	0.8108***	0.8432***
t-stat	-0.36	-1.37	-1.72	-2.56	-5.18		7.01	7.89	7.77	7.79	8.20
4	-0.0034	-0.0085*	-0.0142**	-0.0169***	-0.0260***		0.7790***	0.6307***	0.9225***	0.7167***	0.7866***
t-stat	-0.57	-1.71	-2.57	-3.08	-5.00		6.40	6.26	8.19	6.42	7.43
5 (Small)	-0.0053	0.0015	-0.0004	0.0112	0.0050		0.7858***	0.5187***	0.7272***	0.5596***	0.8328***
t-stat	-1.03	0.22	-0.06	1.24	0.70		7.48	3.68	4.88	3.04	5.80
			SMB						**HML**		
1 (Big)	-0.3185	-0.0519	-0.0252	-0.0722	-0.0184		0.8731***	0.2318***	0.1645**	-0.0070	-0.1904**
t-stat	-1.17	-0.44	-0.25	-0.71	-0.15		4.43	2.73	2.22	-0.10	-2.19
2	0.0246	0.0642	0.1330	0.2508*	0.2148		0.5568***	0.1960*	0.0840	-0.0609	-0.3336***
t-stat	0.14	0.46	0.91	1.73	1.34		4.39	1.96	0.79	-0.58	-2.87
3	0.1801	0.4106**	0.5703***	0.5766***	0.8309***		0.3429***	0.1759	-0.2348*	-0.4083***	-0.5435***
t-stat	1.01	2.44	3.11	3.05	4.45		2.66	1.44	-1.77	-2.98	-4.02
4	0.8243***	0.7633***	1.1204***	0.9454***	1.3606***		0.5140***	0.0114	-0.1309	-0.2085	-0.5943***
t-stat	3.73	4.17	5.48	4.66	7.08		3.21	0.09	-0.88	-1.42	-4.27
5 (Small)	1.5480***	1.1980***	1.2186***	1.1876***	1.6885***		1.0776***	0.3475*	-0.0537	-0.5098**	-0.4641**
t-stat	8.12	4.67	4.50	3.55	6.48		7.80	1.87	-0.27	-2.10	-2.46
			HIMLI								
1 (Big)	0.4137**	0.0485	0.1060	0.1681**	0.2165**						
t-stat	2.07	0.56	1.41	2.24	2.45						
2	0.3811***	0.2883***	0.3888***	0.3873***	0.4184***						
t-stat	2.96	2.84	3.61	3.63	3.55						
3	0.5075***	0.3460***	0.4929***	0.4460***	0.2587*						
t-stat	3.88	2.80	3.65	3.21	1.88						
4	0.2291	0.5536***	0.2959*	0.5497***	0.1683						
t-stat	1.41	4.12	1.97	3.68	1.19						
5 (Small)	0.0677	0.5274***	0.3683*	0.6820***	-0.1188						

t-stat	0.48	2.80	1.85	2.77	-0.62						
			R^2						**BIC**		
1 (Big)	62.95%	82.54%	86.27%	87.07%	84.17%		-2.94	-4.62	-4.89	-4.90	-4.57
2	72.81%	78.05%	75.63%	80.61%	78.92%		-3.82	-4.29	-4.17	-4.19	-3.99
3	71.77%	73.11%	78.27%	76.93%	76.80%		-3.78	-3.90	-3.72	-3.66	-3.69
4	67.25%	79.77%	78.91%	79.88%	79.96%		-3.35	-3.73	-3.51	-3.52	-3.63
5 (Small)	82.26%	71.81%	68.15%	65.10%	66.10%		-3.65	-3.06	-2.95	-2.52	-3.02

Note. This table reports the pricing of the market factor, the size factor and the book-to-market equity factor and the idiosyncratic volatility factor in 25 Fama and French size and BE/ME portfolios.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

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3.4.2. TIME SERIES REGRESSION RESULTS: PRICING IDIOSYNCRATIC VOLATILITY IN THE RETURNS OF 25 VALUE WEIGHTED PORTFOLIOS

Previous studies suggest the effect of idiosyncratic volatility is more pronounced with small stocks (for example Bali et al., 2005). Therefore HIMLI should play a more important role in explaining the returns of equally-weighted stock portfolios than value-weighted portfolios because the small stocks are given equal weights to the big stocks in the equal-weighted portfolios. In Section 3.4.1., the results suggest HIMLI explains the variation in the returns of 25 size and BE/ME portfolios. However, the explanatory power of HIMLI may be weakened when explaining the returns of value-weighted stock portfolios as bigger stocks are given bigger weights in the value-weighted stock portfolios. Therefore, it is important to further examine whether HIMLI explains the variation in returns of value-weighted portfolios.

Twenty-five value weighted size and BE/ME portfolios are constructed to examine the pricing of HIMLI. Table 3.7 presents the regression results of the three-factor model based on 25 value-weighted size and BE/ME portfolios. Consistent with the results of Table 3.5 and 3.6, the coefficients of RMRF are all positive and significant, suggesting that the market factor captures variation in the returns of value weighted portfolios. There are decreasing patterns in the coefficients when moving from big size stocks to small size stocks. Interestingly, SMB does not explain the variation in the returns of the biggest size stock quintile but explains variation in the returns of size quintiles 2 to 5.

Comparing Table 3.7 with Table 3.5, the results in Table 3.5 show 3 out of 5 significant coefficients for largest size quintile. This implies that SMB captures variation in the returns of largest size and medium to low BE/ME portfolios, but SMB does not capture any variation in the returns of largest size quintile in Table 3.7. This suggests that SMB does not relate to the returns of largest stocks listed on the ASX, but the returns of these largest stocks can be explained by the market factor and the HML factor. There are 16 out of 25 significant coefficients for HML. Similar to Table 3.5, the HML coefficients are related to BE/ME as the highest BE/ME quintile shows positive coefficients and the lowest BE/ME quintile shows negative coefficients. There are no obvious patterns in the coefficients of HML when moving from the big size quintile to the small size quintile. These findings are consistent with the results in Table 3.5 and those of Fama and French (1993). Adjusted R-squared values are high as 17 out of 25 values are greater than 70%. The lowest adjusted R-squared value is 58.3% and the highest adjusted R-squared value is 85.33% indicating that the model explains significant variation in the returns of the 25 size and BE/ME portfolios.

Table 3.8 presents the regression results of a four factor model based on 25 value-weighted size and BE/ME portfolios. RMRF shows consistent explanatory power in the returns of 25 size and BE/ME portfolios. Consistent with the results of Table 3.5, 3.6 and 3.7, there are decreasing trends in the coefficients of RMRF when moving from big size quintile to small size quintile, but there are no apparent trends in the coefficients when moving across the BE/ME quintiles.

The results in Table 3.8 also report 15 out of 25 significant coefficients for SMB compared to 20 out of 25 significant coefficients in Table 3.7. There is an increasing trend in the coefficients when moving from the big size quintile to the small size quintile (size quintile 3 to size quintile 5) which suggests that coefficients of SMB are related to size as the returns of smaller size quintiles are more sensitive to changes in SMB. There are not major changes in the coefficients of HML after adding HIMLI into the model compared to Table 3.7 as number of significant coefficients of HML reduces from 16 in Table 3.7 to 14 in Table 3.8 and some very minor changes in magnitude of the coefficients. Coefficients of HML are related to BE/ME as highest BE/ME quintile has the largest coefficients and the lowest BE/ME quintile has the lowest coefficients. HIMLI also explains variation in the returns of value-weighted size and BE/ME stock portfolios as there are 17 out of 25 significant HIMLI coefficients.

Interestingly, when comparing Table 3.8 with Table 3.6, the results indicate that HIMLI does not explain any variation in the returns of the largest value weighted stock portfolios but explains some variation in the returns of the largest equally weighted stock portfolios. This confirms that the effect of idiosyncratic volatility is more pronounced with smaller stocks than the largest stocks and it does not related to the largest stocks listed on the ASX. Moreover, the results indicate that to some extent HIMLI captures similar information in the stock returns as that captured by SMB.

Table 3.7 Fama and French three-factor model: 25 value-weighted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + \varepsilon_t$$

	BE/ME										
Size	**1 (High)**	**2**	**3**	**4**	**5 (Low)**		**1 (High)**	**2**	**3**	**4**	**5 (Low)**
			Alpha						**RMRF**		
1 (Big)	-0.0128*	-0.0059*	-0.0112***	0.0035	0.0056*		1.2845***	1.0297***	0.9733***	1.0121***	0.9570***
t-stat	-1.81	-1.73	-3.35	1.34	1.73		11.42	19.14	18.47	24.75	18.83
2	-0.0079	-0.0087**	-0.0046	-0.0097**	-0.0132***		1.0721***	1.0137***	0.9386***	1.0655***	1.1067***
t-stat	-1.53	-2.32	-1.13	-2.25	-2.91		13.22	17.14	14.51	15.69	15.44
3	-0.0009	-0.0047	-0.0073	-0.0133**	-0.0274***		0.9564***	0.9080***	1.0376***	1.0375***	0.9891***
t-stat	-0.17	-1.00	-1.36	-2.47	-5.19		11.49	12.23	12.27	12.22	11.86
4	-0.0049	-0.0081	-0.0142**	-0.0175***	-0.0268***		0.8596***	0.8446***	1.0731***	0.9852***	0.8828***
t-stat	-0.84	-1.57	-2.59	-3.07	-4.73		9.34	10.39	12.38	10.91	9.86
5 (Small)	-0.0054	-0.0026	-0.0007	0.0045	-0.0053		0.9013***	0.8070***	0.8949***	0.8322***	0.7366***
t-stat	-1.01	-0.34	-0.09	0.49	-0.79		10.73	6.63	8.04	5.80	6.88
			SMB						**HML**		
1 (Big)	0.1293	-0.0601	-0.0273	-0.0764	0.0733		0.7598***	0.2899***	0.3650***	-0.0212	-0.2889***
t-stat	0.92	-0.89	-0.41	-1.49	1.15		4.07	3.24	4.17	-0.31	-3.42
2	0.4691***	0.3605***	0.6195***	0.6502***	0.6336***		0.4313***	0.1149	-0.0482	-0.1004	-0.4689***
t-stat	4.62	4.87	7.65	7.65	7.06		3.20	1.17	-0.45	-0.89	-3.94
3	0.7588***	0.7341***	1.0616***	1.0012***	1.0654***		0.2499*	0.0875	-0.3041**	-0.4089***	-0.5009***
t-stat	7.28	7.90	10.03	9.42	10.21		1.81	0.71	-2.16	-2.90	-3.62
4	1.0370***	1.3958***	1.4586***	1.4550***	1.5765***		0.4859***	-0.0869	-0.2176	-0.2620*	-0.6798***
t-stat	9.01	13.72	13.44	12.87	14.07		3.18	-0.64	-1.51	-1.75	-4.57
5 (Small)	1.5791***	1.8802***	1.6563***	2.0254***	1.5817***		0.7305***	0.1447	-0.2294	-0.6689***	-0.3841**
t-stat	15.02	12.35	11.89	11.27	11.80		5.23	0.72	-1.24	-2.80	-2.16
			R^2						**BIC**		
1 (Big)	58.30%	77.83%	76.97%	85.33%	78.58%		-3.04	-4.51	-4.55	-5.06	-4.63
2	68.39%	77.00%	74.84%	77.08%	76.87%		-3.69	-4.32	-4.14	-4.05	-3.94
3	67.63%	70.35%	74.26%	73.44%	74.31%		-3.64	-3.87	-3.61	-3.60	-3.64
4	66.74%	77.01%	79.22%	76.45%	77.70%		-3.44	-3.69	-3.56	-3.48	-3.49
5 (Small)	80.59%	68.55%	69.82%	64.44%	67.69%		-3.62	-2.88	-3.06	-2.55	-3.13

Note. This table reports the pricing of the market factor, the size factor and the book-to-market equity factor in 25 Fama and French size and BE/ME portfolios.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3.8 Fama and French three-factor model augmented by an idiosyncratic volatility factor: 25 value-weighted portfolios $r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHML_t + iHIMLI_t + \varepsilon_t$

	BE/ME										
Size	**1 (High)**	**2**	**3**	**4**	**5 (Low)**		**1 (High)**	**2**	**3**	**4**	**5 (Low)**
			Alpha						**RMRF**		
1 (Big)	-0.0130*	-0.0059*	-0.0112***	0.0035	0.0055*		1.1626***	1.0491***	0.9746***	1.0427***	0.9318***
t-stat	-1.83	-1.71	-3.34	1.35	1.71		8.06	15.08	14.29	19.78	14.19
2	-0.0081	-0.0088**	-0.0048	-0.0099**	-0.0134***		0.9148***	0.8885***	0.7739***	0.9063***	0.9127***
t-stat	-1.61	-2.43	-1.24	-2.38	-3.11		8.96	12.01	9.71	10.75	10.41
3	-0.0012	-0.0049	-0.0076	-0.0136***	-0.0276***		0.7029***	0.7385***	0.8030***	0.8136***	0.8241***
t-stat	-0.24	-1.08	-1.49	-2.65	-5.35		7.02	8.00	7.79	7.81	7.86
4	-0.005	-0.0084*	-0.0144***	-0.0179***	-0.0268***		0.7567***	0.5850***	0.9427***	0.7222***	0.8634***
t-stat	-0.86	-1.76	-2.65	-3.32	-4.71		6.41	6.03	8.54	6.60	7.45
5 (Small)	-0.0055	-0.003	-0.0009	0.0041	-0.0053		0.7649***	0.5213***	0.7244***	0.5071***	0.7369***
	-1.06	-0.40	-0.12	0.46	-0.78		7.17	3.45	5.12	2.84	5.32
			SMB						**HML**		
1 (Big)	-0.1673	-0.0128	-0.0242	-0.0019	0.0121		0.8093***	0.2821***	0.3645***	-0.0337	-0.2787***
t-stat	-0.64	-0.10	-0.20	-0.02	0.10		4.26	3.08	4.06	-0.49	-3.23
2	0.0865	0.056	0.2187	0.2628*	0.1614		0.4951***	0.1657*	0.0187	-0.0358	-0.3901***
t-stat	0.47	0.42	1.51	1.72	1.01		3.69	1.70	0.18	-0.32	-3.38
3	0.1419	0.3216**	0.4909**	0.4563**	0.6641***		0.3528***	0.1563	-0.2089	-0.3179**	-0.4339***
t-stat	0.78	1.92	2.62	2.41	3.49		2.68	1.29	-1.54	-2.32	-3.15
4	0.7867***	0.7641***	1.1415***	0.8150***	1.5292***		0.5277***	0.0185	-0.1646	-0.1553	-0.6719***
t-stat	3.67	4.34	5.70	4.10	7.27		3.40	0.15	-1.13	-1.08	-4.41
5 (Small)	1.2471***	1.1848***	1.2417***	1.2343***	1.5824***		0.7858***	0.2607	-0.1601	-0.5369**	-0.3842*
t-stat	6.44	4.32	4.83	3.80	6.29		5.60	1.31	-0.86	-2.28	-2.11
			HIMLI								
1 (Big)	0.2583	-0.0411	-0.0028	-0.0649	0.0533						
t-stat	1.34	-0.44	-0.03	-0.92	0.61						
2	0.3332**	0.2652***	0.3490***	0.3373***	0.4112***						
t-stat	2.44	2.68	3.28	3.00	3.51						
3	0.5371***	0.3592***	0.4970***	0.4745***	0.3495**						
t-stat	4.01	2.91	3.61	3.41	2.50						
4	0.218	0.5500***	0.2761*	0.5573***	0.0412						
t-stat	1.38	4.24	1.87	3.81	0.27						
5 (Small)	0.2890**	0.6055***	0.3611*	0.6888***	-0.0005						

t-stat	2.03	3.00	1.91	2.89	0.00						
			R^2						**BIC**		
1 (Big)	58.62%	77.65%	76.74%	85.31%	78.45%		-3.01	-4.47	-4.51	-5.02	-4.59
2	69.84%	78.30%	77.00%	78.71%	79.14%		-3.70	-4.35	-4.20	-4.09	-4.01
3	71.74%	72.34%	76.92%	75.90%	75.54%		-3.74	-3.90	-3.68	-3.66	-3.65
4	67.03%	80.24%	79.71%	79.16%	77.50%		-3.41	-3.80	-3.55	-3.56	-3.45
5 (Small)	81.15%	70.80%	70.57%	66.78%	67.37%		-3.62	-2.92	-3.05	-2.58	-3.09

Note. This table reports the pricing of the market factor, the size factor and the book-to-market equity factor and the idiosyncratic volatility factor in 25 Fama and French size and BE/ME portfolios.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

3.4.3. DISCUSSION FOR THE TREND IN THE COEFFICIENTS OF RMRF

Generally, there are decreasing patterns in the coefficients of RMRF when moving from bigger size quintiles to smaller size quintiles in Tables 3.5 to 3.8. This suggests that the returns of bigger size Australia stocks are more sensitive to changes in the returns of RMRF. In other words, these decreasing patterns suggest that big size stocks are systematically riskier than small size stocks.

This is an interesting finding as conventional wisdom suggests that big size stocks are less risky than small size stocks so that big size stocks should have smaller coefficients than small size stocks. However, Kamara, Lou and Sadka (2010) find that market risk increased significantly for large firms but declined significantly for small firms over the period 1963 to 2008 in the US and small firms were less sensitive to market risk than large firms from 1981 to 2008. They suggest that the increase in sensitivity to market risk for large firms is due to the concentration in institutional investments in large stocks as institutional investors tend to invest more heavily in prudent and large stocks which lead to under investment in small and less prudent stocks (see Del Guercio, 1996). In Australia, it was evident that the top 100 largest companies listed on the Australian Securities Exchange made up approximately 74% of the Australian stock market by market capitalization in 2011[10]. It is interesting but not surprising that institutional investors under-invest in small stocks in Australia which leads to lower sensitivity to market risk for small stocks than big stocks.

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[10] http://www.spindices.com/indices/equity/sp-asx-100

3.4.4. FAMA-MacBeth (1973) CROSS-SECTIONAL REGRESSION RESULTS

The cross-sectional relationship between the Australian stock returns and HIMLI is examined by using Fama-MacBeth (1973) regressions. In the cross-sectional analysis, the sample period has been extended, beginning in January 1993 and ending in December 2010 since there are sufficient stocks in the portfolio because the stocks are not required to sort into the 25 portfolios. Table 3.9 reports Fama-MacBeth (1973) regression results. Model 1 of Table 3.9 regresses the excess return on the market beta (see equation (3.4) in section 3.3.6.). The market beta coefficient is significant and negative which suggests the market beta explains cross-sectional returns of Australian stocks. Model 2 regresses the excess return on the market beta and HIMLI (see equation (3.5) in section 3.3.6.). The coefficient of HIMLI is significant and positive which suggests that idiosyncratic volatility is positively related to the returns of Australian stocks cross-sectionally. This supports the hypothesis that high idiosyncratic volatility stocks should have high returns as investors require compensation for holding high idiosyncratic volatility stocks. Model 3 regresses the excess return on market beta, size, BE/ME and HIMLI (see equation (3.6) in section 3.3.6.). The coefficients of market beta, size and the idiosyncratic volatility factor are significant, but the coefficient of BE/ME is not. The Fama-MacBeth (1973) regression results show that HIMLI is priced for Australian stocks returns from January 1993 to December 2010 even after controlling for the size and the BE/ME factors. The cross-sectional regression results suggest that the HIMLI factor has greater explanatory power for Australian stock returns over the sample period than the size and BE/ME factors because there is big increase in adjusted R-squared value after the HIMLI factor is included in the cross-sectional regression models.

Table 3.9 Fama and Macbeth (1973) cross-sectional regressions: The pricing of the HIMLI factor

Model	Alpha	Beta	Size	BE/ME	Idiovol	R^2
1	-0.0405***	-0.0333***				64%
t-stat	-4.16	6.11				
2	0.0209***	-0.0136**			0.0134***	95%
t-stat	5.62	-3.31			7.05	
3	0.025***	-0.0252***	0.0094*	0.0044	0.0153***	98%
t-stat	9.74	-5.33	2.32	0.6	12.19	

Note. This table shows the regressions results of Fama and Macbeth cross-sectional regressions.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

3.4.5. TIME SERIES REGRESSION RESULTS: PRICING OF IDIOSYNCRATIC VOLATILITY IN TEN IDIOSYNCRATIC VOLATILITY SORTED PORTFOLIOS

Table 3.10 reports the results for pricing of the idiosyncratic volatility factor in ten idiosyncratic volatility sorted portfolios. A two-factor model comprising of a market risk factor and the idiosyncratic volatility factor is employed.

The results show the intercepts are statistically significant in 3 out of 10 cases and all have positive signs. Specifically, the highest (Portfolio 1) and lowest idiosyncratic volatility portfolios (Portfolios 9 and 10) each report significant intercepts suggesting large positive abnormal returns.

All market risk factor coefficients are statistically significant and positive as expected. These coefficients do not demonstrate a pattern when moving from high idiosyncratic volatility portfolios to low idiosyncratic volatility portfolios.

The idiosyncratic volatility factor coefficients decrease monotonically when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio. This suggests that the higher the idiosyncratic volatility of the portfolio, the more sensitive the changes in return to changes in the idiosyncratic volatility factor.

The returns of the idiosyncratic volatility portfolios are strongly and positively related to the idiosyncratic volatility factor except in the case of portfolio 10. This indicates that the idiosyncratic volatility factor captures variation in stock returns that is missed by the market risk factor and therefore suggests that the market factor alone cannot explain the variation in the stock excess returns. The adjusted R-squared also exhibits a decreasing pattern from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio.

The adjusted R-squared is above 50% for all portfolios except portfolio 10. This indicates that the two factor model captures large proportions of variation in returns from portfolio 1 to portfolio 9, with the only exception being the lowest idiosyncratic volatility portfolio.

Table 3.10 Two-factor model: the pricing of HIMLI factor in 10 idiosyncratic volatility sorted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + iHIMLI + \varepsilon_t$$

	2-Factor Model			
Portfolio	**Alpha**	**RMRF**	**HIMLI**	**R^2**
1(high)	0.0207***	0.5542***	1.1314***	67%
t-stat	-4.4	-4.69	-17.54	
2	0.0001	0.7387***	0.8976***	75%
t-stat	-0.03	-8.77	-19.53	
3	0	0.8213***	0.7310***	71%
t-stat	-0.01	-10.01	-16.32	
4	-0.0028	0.7955***	0.6001***	67%
t-stat	-0.91	-10.19	-14.08	
5	-0.0016	0.7532***	0.4624***	66%
t-stat	-0.60	-11.11	-12.5	
6	-0.0026	0.8753***	0.2825***	67%
t-stat	-1.12	-14.92	-8.82	
7	-0.0001	0.8492***	0.1664***	66%
t-stat	-0.07	-16.54	-5.94	
8	0.0023	0.7567***	0.0784***	57%
t-stat	-1.13	-14.91	-2.83	
9	0.0053***	0.6434***	0.0722***	52%
t-stat	-2.75	-13.34	-2.74	
10(low)	0.0133***	0.3595***	-0.0004	6%
t-stat	-3.57	-3.83	-0.01	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility in the previous year. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3.11 and Table 3.12 present the results of two three-factor models. In Table 3.11, the three-factor model comprises a market risk factor, a size factor and the idiosyncratic volatility factor. Table 3.11 shows the coefficients of this three-factor model and several important findings are observed. First, in 7 out of 10 cases, the intercepts are significant and 5 of these have negative signs. Second, as expected, all coefficients of the market risk factor are positive and significant and do not exhibit any pattern. The coefficients of the market factor for portfolio 2 to 8 are very close to 1and portfolio 1 and 10 have smaller coefficients than other portfolios. Third, the coefficients of the size factor are positive and significant. There is a monotonically decreasing pattern in the coefficients from portfolio 3 to portfolio 8 and portfolios 1 and 2 have bigger coefficients than portfolio 10. This indicates that excess returns of the high idiosyncratic volatility portfolios are more sensitive to the changes in the size factor than low idiosyncratic volatility portfolios. Fourth, in 8 out of 10 cases, the idiosyncratic volatility factor has significant and positive coefficients. A monotonically decreasing pattern in the coefficients is evident when moving from high idiosyncratic volatility portfolios to low idiosyncratic volatility portfolios, and the lowest idiosyncratic volatility portfolios have negative coefficients. This indicates that the idiosyncratic volatility factor is priced and it captures the great variations in the excess returns of the idiosyncratic volatility portfolios. The adjusted R-squared shows a decreasing pattern again, but the values of adjusted R-squared of this three-factor model are greater than the adjusted R-squared values of the two-factor model. This suggests that there is an increase in the proportion of variation explained by the three-factor model.

Table 3.11 Three-factor model: the pricing of HIMLI factor in 10 idiosyncratic volatility sorted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB + iHIMLI + \varepsilon_t$$

		3-Factor Model			
Portfolio	**Alpha**	**RMRF**	**SMB**	**HIMLI**	R^2
1(high)	0.0161***	0.6856***	0.6402***	0.8812***	69%
t-stat	3.46	5.79	4.13	10.15	
2	-0.0066**	0.9323***	0.9426***	0.5292***	83%
t-stat	-2.31	12.88	9.94	9.96	
3	-0.0074***	1.0335***	1.0333***	0.3272***	83%
t-stat	-2.83	15.65	11.94	6.75	
4	-0.0089***	0.9708***	0.8538***	0.2665***	77%
t-stat	-3.32	14.31	9.60	5.35	
5	-0.0068***	0.9042***	0.7354***	0.1750***	76%
t-stat	-2.93	15.30	9.49	4.04	
6	-0.0061***	0.9763***	0.4915***	0.0904**	72%
t-stat	-2.79	17.63	6.77	2.23	
7	-0.0028	0.9259***	0.3735***	0.0205	70%
t-stat	-1.42	18.63	5.73	0.56	
8	0.0002	0.8170***	0.2938***	-0.0365	61%
t-stat	0.10	16.18	4.44	-0.98	
9	0.0025	0.7238***	0.3916***	-0.0808**	60%
t-stat	1.38	15.80	6.52	-2.40	
10(low)	0.0101***	0.4522***	0.4513***	-0.1767**	11%
t-stat	2.71	4.77	3.63	-2.54	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3.12 shows the coefficients of a three-factor model that comprises a market risk factor, a book-to-market equity factor and an idiosyncratic volatility factor. First, surprisingly, the highest and lowest idiosyncratic volatility portfolios have significant positive intercepts which indicate abnormal returns are only available on two extreme cases. Second, as expected, the factor loadings of the market risk factor are significant and positive.

There is no pattern when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio. Third, in 3 out of 10 cases, HML factor has positive and significant coefficients. Fourth, again, HIMLI factor has significant and positive coefficients except in the case of portfolio 10. There is a monotonically decreasing pattern in the coefficients. The adjusted R-squared is above 50% except portfolio 10 which indicates that a large proportion of variation is explained by the model. The results from Table 3.11 and 3.12 suggest that the idiosyncratic volatility factor is priced in excess returns of Australian stocks.

Table 3.12 Three-factor model: the pricing of HIMLI factor in 10 idiosyncratic volatility sorted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sHML + iHIMLI + \varepsilon_t$$

		3-Factor Model			
Portfolio	**Alpha**	**RMRF**	**HML**	**HIMLI**	**R^2**
1(high)	0.0190***	0.5633***	0.0863	1.1334***	66%
t-stat	3.27	4.70	0.50	17.50	
2	0.0030	0.7234***	-0.1458	0.8940***	75%
t-stat	0.73	8.50	-1.20	19.43	
3	-0.0028	0.8359***	0.1388	0.7344***	71%
t-stat	-0.69	10.08	1.17	16.37	
4	-0.0039	0.8013***	0.0552	0.6015***	67%
t-stat	-1.02	10.13	0.49	14.05	
5	-0.0040	0.7661***	0.1220	0.4654***	66%
t-stat	-1.21	11.18	1.24	12.57	
6	-0.0041	0.8835***	0.0778	0.2844***	67%
t-stat	-1.44	14.88	0.91	8.86	
7	-0.0030	0.8645***	0.1453*	0.1699***	66%
t-stat	-1.20	16.76	1.97	6.09	
8	-0.0006	0.7718***	0.1438*	0.0818***	58%
t-stat	-0.22	15.14	1.97	2.97	
9	0.0015	0.6633***	0.1896***	0.0768***	53%
t-stat	0.66	13.80	2.75	2.95	
10(low)	0.0151***	0.3502***	-0.0880	-0.0025	6%
t-stat	3.27	3.68	-0.65	-0.05	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3.13 reports the results of the Fama and French three-factor model. In Table 3.7, there are 6 of 10 cases the intercept is significant and the highest and lowest idiosyncratic volatility portfolios (Portfolio 1 and Portfolio 10 respectively) have the largest positive abnormal returns. Portfolios 4 to 7 show negative abnormal returns. Second, the coefficients of the market factor show consistency as they are significant, positive, and there is no pattern. In 8 out of 10 cases, the coefficients of the market factor are close to 1 which is consistent with many previous studies, including Gaunt (2004). Third, SMB factor has significant and positive coefficients, and there is a monotonically decreasing pattern when moving from portfolio 1 to portfolio 10. This indicates that SMB factor captures the variation in excess returns of the portfolios. Fourth, the explanatory power of HML is low once again. In 4 out of 10 cases, the coefficients are significant with a negative signs for the high idiosyncratic volatility portfolios. The Adjusted R-squared values are high except for portfolio 10.

Table 3.13 Fama and French three-factor model: the pricing of HIMLI factor in 10 idiosyncratic volatility sorted portfolios

$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB + hHML + \varepsilon_t$,

				FF 3-Factor Model			
Portfolio	**Monthly Excess Return**	**Std Dev**	**Alpha**	**RMRF**	**SMB**	**HML**	**R^2**
1(high)	4.83%	15.28%	0.0205***	1.1408***	1.7572***	-0.3307*	54%
t-stat			3.02	8.59	13.01	-1.65	
2	1.81%	9.57%	0.0018	1.1683***	1.6313***	-0.5062***	77%
t-stat			0.44	15.00	20.59	-4.31	
3	1.57%	8.71%	-0.0049	1.1966***	1.4509***	-0.1715*	79%
t-stat			-1.42	17.86	21.29	-1.70	
4	1.07%	7.79%	-0.0057*	1.0963***	1.1974***	-0.2001**	74%
t-stat			-1.67	16.52	17.75	-2.00	
5	0.95%	6.62%	-0.0057**	0.9929***	0.9581***	-0.0796	74%
t-stat			-1.98	17.51	16.61	-0.93	
6	0.62%	5.81%	-0.0054**	1.0212***	0.6070***	-0.0481	72%
t-stat			-2.04	19.69	11.51	-0.62	
7	0.67%	5.02%	-0.0041*	0.9454***	0.3952***	0.0659	70%
t-stat			-1.73	20.55	8.45	0.95	
8	0.72%	4.43%	-0.0016	0.8085***	0.2426***	0.0989	61%
t-stat			-0.66	17.32	5.11	1.40	
9	0.96%	3.98%	0.0000	0.6954***	0.2827***	0.1404**	60%
t-stat			0.02	16.34	6.53	2.19	
10(low)	1.51%	5.55%	0.0127***	0.3385***	0.2380***	-0.1181	9%
t-stat			2.80	3.80	2.63	-0.80	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

The regression results based on a four-factor model are reported in Table 3.14. A four-factor model comprises a market factor, a size factor, a BE/ME factor and an idiosyncratic volatility factor. Consistent with the results of the Fama and French three-factor model, the four-factor model explains a greater proportion of the variation in the excess return of the portfolios. This is evidenced by high adjusted R-squared values. The intercepts, coefficients of the market risk factor, size factor and BE/ME factor exhibit similar results as the Fama and French three-factor model. The interesting finding is that the idiosyncratic volatility factor is priced in this four-factor model and there is a monotonically decreasing pattern in coefficients when moving from highest idiosyncratic volatility portfolio (Portfolio 1) to the lowest idiosyncratic volatility portfolio (Portfolio 10). Both coefficients of the size factor and the idiosyncratic volatility factor show monotonically decreasing patterns and these two factors capture most of variations of excess returns. The excess returns of high idiosyncratic volatility portfolios are positively related to the idiosyncratic volatility factor, while excess returns of the bottom two portfolios are negatively related to the idiosyncratic volatility factor.

These results suggest idiosyncratic volatility was priced for Australian stock returns from 1993 to 2010. High (low) idiosyncratic volatility stocks are small (big) by size, have big (small) factor loadings on the size factor and idiosyncratic volatility factor. The HML factor has weaker explanatory power than SMB factor and HIMLI factor to the returns of Australian stocks.

Table 3.14 Fama and French three-factor model augmented by an idiosyncratic volatility factor: the pricing of HIMLI factor in 10 idiosyncratic volatility sorted portfolios

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB + hHML + iHIMLI + \varepsilon_t$$

					4-Factor Model			
	Excess Return	**Std Dev**	**Alpha**	**RMRF**	**SMB**	**HML**	**HIMLI**	R^2
1 (high)	4.83%	15.28%	0.0169***	0.6828***	0.6470***	-0.0399	0.8775***	69%
t-stat			3.00	5.73	4.09	-0.24	9.93	
2	1.81%	9.57%	-0.0003	0.9084***	1.0013***	-0.3412***	0.4980***	84%
t-stat			-0.08	12.80	10.64	-3.40	9.46	
3	1.57%	8.71%	-0.0062**	1.0289***	1.0445***	-0.0650	0.3213***	83%
t-stat			-1.97	15.48	11.85	-0.69	6.52	
4	1.07%	7.79%	-0.0068**	0.9628***	0.8736***	-0.1153	0.2560***	77%
t-stat			-2.10	14.13	9.67	-1.20	5.07	
5	0.95%	6.62%	-0.0064**	0.9027***	0.7392***	-0.0223	0.1730***	76%
t-stat			-2.29	15.17	9.36	-0.27	3.92	
6	0.62%	5.81%	-0.0058**	0.9749***	0.4948***	-0.0187	0.0887**	72%
t-stat			-2.19	17.48	6.69	-0.24	2.15	
7	0.67%	5.02%	-0.0042*	0.9311***	0.3606***	0.0749	0.0273	70%
t-stat			-1.77	18.65	5.44	1.06	0.74	
8	0.72%	4.43%	-0.0015	0.8233***	0.2784***	0.0895	-0.0283	61%
t-stat			-0.61	16.24	4.14	1.25	-0.75	
9	0.96%	3.98%	0.0003	0.7320***	0.3715***	0.1172*	-0.0701**	60%
t-stat			0.15	15.98	6.11	1.81	-2.06	
10 (low)	1.51%	5.55%	0.0135***	0.4394***	0.4826***	-0.1822	-0.1934***	12%
t-stat			3.01	4.62	3.82	-1.36	-2.74	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

3.4.6. IS IDIOSYNCRATIC VOLATILITY PRICED CONDITIONAL ON BUSINESS CYCLES?

Previous studies have investigated the behaviour of idiosyncratic volatility in different market cycles. For example, Campbell et al. (2001) find that idiosyncratic volatility decreases during economy downturns, while Ooi et al. (2009) report that idiosyncratic volatility increases dramatically during bad market times but decreases marginally during good market times. It is evident that differences in behaviour of idiosyncratic volatility during different business cycles may affect the pricing ability of the idiosyncratic volatility factor. Therefore, the analysis is further extended in this chapter to investigate the pricing ability of the idiosyncratic volatility factor during market expansions and contractions.

Business Cycle phases in the Australian market are classified based on the definitions produced by the Melbourne Institute of Applied Economic and Social Research. Table 3.15 presents a summary of these phases over the sample period. There are a total of 144 months of expansion and 72 months of recession. An expansion dummy variable and a contraction dummy are generated base on the information provided by Table 3.15 and a two-factor model is employed to test the stability of the pricing ability of the idiosyncratic volatility factor. The two-factor model comprises a market factor and an idiosyncratic volatility factor. The two-factor model is selected among all the models used in this study because the market risk factor is the most stable pricing factor.

Table 3.15 Phases of Australian Business Cycle over the Sample Period

Start month	End month	Phases of Business Cycle	Number of months
Jan-93	Aug-95	Expansion	32
Sep-95	Feb-97	Contraction	18
Mar-97	Jun-00	Expansion	40
Jul-00	Feb-01	Contraction	8
Mar-01	May-04	Expansion	39
Jun-04	Feb-06	Contraction	21
Mar-06	Jan-07	Expansion	11
Feb-07	Feb-09	Contraction	25
Mar-09	Dec-10	Expansion	22

Source: original data is downloaded from website of Melbourne Institute of Applied Economic and Social Research. Website address: [http://melbourneinstitute.com/macro/reports/bachronologyhtml]

Table 3.16 reports the coefficients for the two asset pricing factors during expansions and contractions. During expansions, 3 out of 10 intercepts are statistically significant. The intercepts are positive and evident for the highest and lowest idiosyncratic volatility portfolios. There is no pattern in the coefficients of the market factor. They are all significantly different from zero. In 9 out of 10 cases, the coefficients of the idiosyncratic volatility factor are significant and positive, except the coefficient for portfolio 10. A monotonically decreasing pattern in the coefficients is observed which suggests that the idiosyncratic volatility factor is priced and captures the variation in the excess returns of the portfolios during expansions. The adjusted R-squared values are lower than those presented in Table 3.10, but they are all above 30% except R-squared for portfolio 10 which suggests that the two-factor model captures the variations in the excess returns of portfolio 1 to 9.

During contractions, there are 9 significant intercepts. Hence, the two-factor model exhibits greater mispricing during contractions than during expansions. All the coefficients of the market factor are significant and positive. There is no pattern in the coefficients of the market factor. The coefficients of the idiosyncratic volatility factor show a monotonically decreasing pattern from portfolio 1 to portfolio 7. The adjusted R-squared values are much lower than those of the two-factor model during expansions. Based on the results provided in Table 3.16, the idiosyncratic volatility factor is priced in both expansions and contractions, but the two-factor model explains more variations in the excess returns of ten idiosyncratic volatility sorted portfolios in economic expansions than in economic contractions.

Further evidence on robustness of the effect of idiosyncratic volatility during different phases of the economy is presented in Appendix 1.

Table 3.16 Two-factor model: pricing of idiosyncratic volatility based on economic conditions

$$r_t - r_{ft} = \alpha + \beta D_{expansion}(r_{mt} - r_{ft}) + iD_{expansion} HIMLI + \varepsilon_t$$

$$r_t - r_{ft} = \alpha + \beta D_{contraction}(r_{mt} - r_{ft}) + iD_{contraction} HIMLI + \varepsilon_t$$

2-Factor Model									
		Expansions					Contractions		
Port folio	Alpha	RMRF	HIMLI	ADJ R-sq		Alpha	RMRF	HIMLI	R^2
1(high)	0.0239***	0.4919***	1.1095***	0.51		0.0389***	0.6541**	1.1766***	14%
t-stat	4.20	2.79	13.10			5.26	1.97	4.53	
2	0.0028	0.6992***	0.8691***	0.55		0.0158***	0.7853***	0.9885***	18%
t-stat	0.62	5.05	13.05			2.68	2.97	4.76	
3	0.0021	0.8626***	0.6842***	0.52		0.0136**	0.6934***	0.9163***	18%
t-stat	0.51	6.60	10.88			2.53	2.88	4.85	
4	-0.0007	0.8023***	0.5438***	0.45		0.0087*	0.7126***	0.8551***	22%
t-stat	-0.17	6.46	9.10			1.85	3.37	5.16	
5	0.0000	0.7642***	0.4195***	0.44		0.0080**	0.6808***	0.6530***	21%
t-stat	0.01	7.19	8.21			1.98	3.77	4.62	
6	-0.0015	0.8418***	0.2638***	0.42		0.0053	0.9170***	0.3604***	23%
t-stat	-0.49	8.87	5.78			1.54	5.89	2.95	
7	0.0006	0.8398***	0.1439***	0.42		0.0060**	0.8400***	0.2688**	24%
t-stat	0.24	10.15	3.62			2.01	6.25	2.55	
8	0.0029	0.7027***	0.0708*	0.32		0.0069***	0.8480***	0.1154	24%
t-stat	1.13	8.95	1.88			2.64	7.19	1.25	
9	0.0054**	0.6201***	0.0831**	0.33		0.0096***	0.7067***	0.0033	18%
t-stat	2.41	8.87	2.47			3.88	6.40	0.04	
10(low)	0.0135***	0.3065**	0.0102	0.03		0.0152***	0.4726***	-0.0520	3%
t-stat	3.53	2.60	0.18			4.07	2.82	-0.40	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. $D_{expansion}$ is a dummy variable which takes a value of unity in the period if expansionary phase of the business cycle is identified by Melbourne Institute of Applied Economic and Social Research and a value of zero otherwise. $D_{contraction}$ is a dummy variable which takes a value of unity in the period if expansionary phase of the business cycle is identified and a value of zero otherwise.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

3.5. CONCLUSION

Investors do not always hold well-diversified portfolios. This could be due to a number of reasons, including high transaction costs, and lack of information. Therefore, idiosyncratic volatility is not fully diversified so investors should be compensated for assuming this type of risk. This chapter examines the role of idiosyncratic volatility in the pricing of Australian stocks from January 2002 to December 2010 in the 25 size and BE/ME sorted portfolios by using time series analysis. The sample period is extended from January 2002 to December 2010 to January 1993 to 2010 for the cross-sectional analysis and time series analysis for the ten idiosyncratic volatility sorted portfolios. The empirical results show that the idiosyncratic volatility factor captures information omitted by the Fama and French three-factor and the idiosyncratic volatility factor is positively related to the returns of Australian stocks when using both time-series and cross-sectional regression analysis.

Another interesting finding is that big stocks are systematically riskier than small stocks in Australia from January 2002 to December 2010. Kamara et al. (2010) find that market risk increased significantly for large firms but declined significantly for small firms over the period 1963 to 2008 in the US and small firms were less sensitive to market risk than large firms from 1981 to 2008. They suggest that the increase in sensitivity to market risk for large firms is due to the concentration in institutional investments in large stocks.

The empirical results also show that the idiosyncratic volatility factor is priced during both economy expansions and contractions. However, the two-factor model explains more variations in the returns of the stocks during expansions than contractions.

The findings of this chapter provide a number of important implications for investors. First, investors may need to consider the level of idiosyncratic volatility remaining in their portfolio if they are not well-diversified when estimating the required rate of return and/or evaluating the performance of these portfolios. Second, investors may need to rebalance their portfolios during different economic phases, specifically expansions and contractions. This is due to the asymmetric behaviour of the idiosyncratic volatility. Holding a constant number of stocks in different phases of business cycle may result in under-diversification of the portfolio as idiosyncratic volatility increases significantly during bad times.

The main goal of this chapter is to explore the pricing role of the idiosyncratic volatility. As the results of this chapter indicate that idiosyncratic volatility is priced for returns of Australian stocks over the sample periods, the pricing of idiosyncratic volatility is further examined by using pension funds in Chapter 4.

CHAPTER 4

4. IDIOSYNCRATIC VOLATILITY AND AUSTRALIAN PENSION FUND RETURNS

4.1. INTRODUCTION

In this chapter, the importance of idiosyncratic volatility in the pricing of Australian Pension funds[11] is examined. Many previous studies have shown that idiosyncratic volatility is priced for stock returns, but studies for the relationship between idiosyncratic volatility and returns of pension funds are rare. An insignificant relationship between idiosyncratic volatility and returns of pension funds is often anticipated, since it is widely accepted in the literature that mutual funds are well diversified. Therefore, idiosyncratic volatility is assumed to be eliminated due to the well diversified portfolios by these funds. However, it is not clear whether idiosyncratic volatility is perfectly eliminated or not. This study uses a comprehensive data set of retail Australian pension funds to examine whether idiosyncratic volatility is important in pricing of Australian pension funds.

The Australian pension fund industry has shown strong growth over past decades. According to the IBIS World Industry Report K7412, it is the fourth largest private pension fund market in the world. Although several previous studies have focused on various aspects of Australian pension funds, no study to date has addressed the issue of

[11] The use of the terms "pension funds" and "superannuation funds" are used interchangeably in this thesis.

idiosyncratic volatility. The findings presented in this chapter suggest that idiosyncratic volatility is important in the pricing of Australian pension funds.

Idiosyncratic volatility for pension funds is defined differently to idiosyncratic volatility for stocks in Chapter 3. Following Angelidis (2010), in this chapter idiosyncratic volatility is defined as the standard deviation of the regression residual from the regression equation of CAPM. The reasons are: (1) this definition is also widely accepted in the literature, (2) more importantly, the definition of idiosyncratic volatility used in Chapter 3 is specific to the stock market, which may not be relevant to some pension funds such as fixed-income funds and allocations funds because these funds do not invest heavily in the stock market. Therefore, a more general definition of idiosyncratic volatility is needed and adopted in this chapter compared to that of Chapter 3.

The research presented in this chapter focuses on three issues. The first issue addresses the question of whether idiosyncratic volatility is priced for Australian pension funds. The second issue looks at whether idiosyncratic volatility is priced for the different categories of pension fund portfolios, such as equity pension funds, fixed-income pension funds and allocation pension funds. The third issue investigates whether the mimicking idiosyncratic volatility factor, pension fund size factor and market factor together capture time-series variations in the returns of pension funds.

Many previous studies (see e.g., Malkiel and Xu, 1997, 2002; Goyal and Santa-Clara, 2003 and Fu, 2009) examine the role of idiosyncratic volatility in asset pricing for exchange listed stocks. Since the implementation of the asset pricing model is not limited to price exchange listed stocks, it is important to understand the role of idiosyncratic volatility in the pricing of pension funds. Moreover, Campbell et al. (2001) find that idiosyncratic volatility has grown over time implying that idiosyncratic volatility has become more difficult to diversify. The implication for fund managers is that in order to maintain a given level of diversification in their portfolios, they may need to increase the number of securities in the portfolios. If pension fund managers are not fully aware of this issue it may lead to under-diversification of their funds. In other words, idiosyncratic volatility is expected to be priced if a significant amount of idiosyncratic volatility remains in their portfolios. Hence, one of the major contributions of this research is that it is the first known study investigating the relationship between Australian pension fund returns and idiosyncratic volatility.

Since strong evidence is found to support the pricing of idiosyncratic volatility in Australian pension fund returns, this study is expanded to test whether an idiosyncratic volatility factor explains the variations in the excess returns of Australian pension fund by constructing an idiosyncratic volatility mimicking factor using pension fund returns and idiosyncratic volatilities. Hence, the second major contribution of this chapter is that a new three-factor model is developed to explain pension fund returns. Following the Fama and French risk factor portfolio mimicking approach in Fama and French (1993), an idiosyncratic volatility mimicking factor and a pension fund size factor are constructed. This pension fund size factor is constructed by using historical pension fund size data, so it contains pension fund specific information in relation to fund size. An idiosyncratic volatility mimicking factor is also constructed by using idiosyncratic volatilities and returns of individual pension funds to mimic the underlying risk in returns in relation to idiosyncratic volatility. Time-series regressions are then employed to explore the relationship between idiosyncratic volatility, pension fund size factor and excess returns of pension funds. The results provide an insight as to whether these pension fund specific risk mimicking factors capture the variation in returns of Australian pension funds.

The results reveal several interesting findings. First, idiosyncratic volatility is priced for returns of Australian Pension Funds. Second, the risk mimicking factors, including both the idiosyncratic volatility factor and the pension fund size factor, play an important role in pricing of Australian Pension funds. More importantly, a three-factor model based on the market factor, fund size factor and idiosyncratic volatility factor have strong explanatory power to the returns of the equity pension funds over the sample period. Overall, the empirical results indicate that idiosyncratic volatility is important in the pricing of pension funds and its effect should not be ignored.

The empirical findings have two practical implications for portfolio managers. First, a three-factor model, consisting of a market factor, a fund size factor and an idiosyncratic volatility factor, can be used to evaluate the performance of equity funds as the model captures great variations in the excess returns of equity pension funds. Second, portfolio managers should match the idiosyncratic volatility of their portfolios with the benchmark portfolio when evaluating the performances of their investment portfolios as idiosyncratic volatility cannot be ignored.

The remainder of this chapter is organized as follows. First, Section 4.2 describes the data. Section 4.3 outlines the methods adopted in this chapter. Section 4.4 summarizes the empirical results. Section 4.5 presents concluding comments.

4.2. DATA AND DESCRIPTIVE ANALYSIS

The data are obtained from several databases. The historical weekly returns, monthly returns and historical annual fund sizes of Australian retail pension funds are supplied by Morningstar database. The historical ASX200 index and UBS Warburg bond index are supplied by the IRESS database. The historical 90-day Bank Acceptable Bill rate is supplied by Reserve Bank of Australia. The sample period is from January 1994 to December 2008.

Figure 4.1 Number of pension funds in each year of the sample period

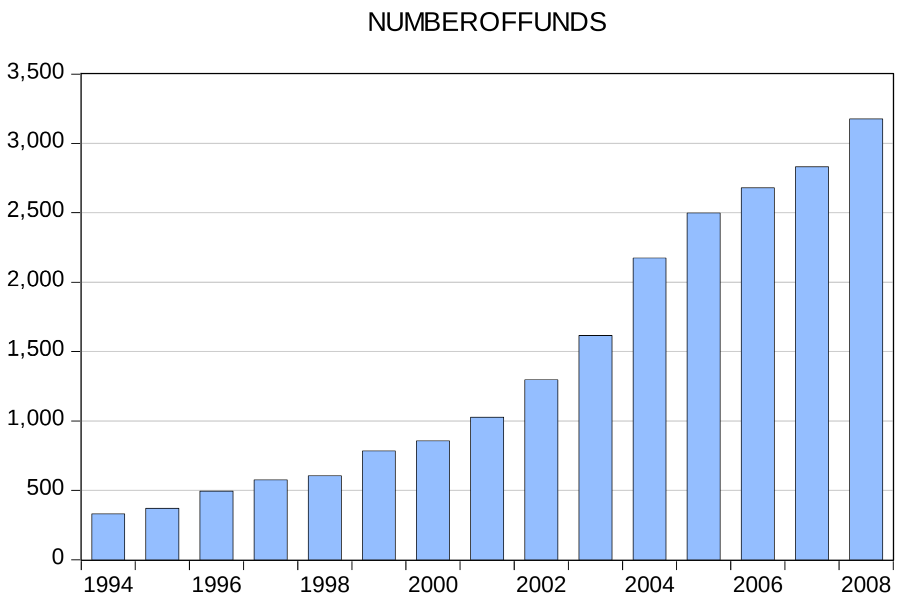


Figure 4.2 Annual average fund size for all pension funds 1994-2008

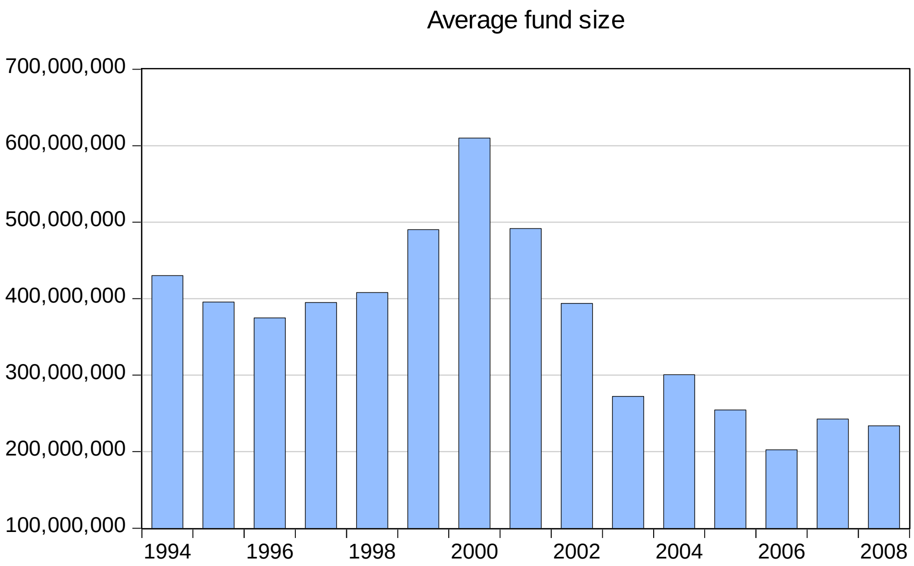


Figure 4.1 shows that the number of pension funds had grown rapidly during the sample period. In order to avoid survivor bias, both live and dead pension funds are included in the sample over the sample period. Therefore, the number of retail pension funds varies across years. At the beginning of the sample period there are 331 funds, but by the end of the sample period the number of funds in the sample has grown to 3171.

Figure 4.2 shows the average fund size over the sample period. The average fund size reached a maximum of AUD $609,814,037 in 2000, and declined until it reached a minimum of AUD $202,604,659 in 2006. This pattern suggests that the new pension funds born after 2000 are relative smaller funds by size. Hence, the number of funds had grown rapidly after 2000, but these new funds are relative smaller in size than old funds.

4.3. METHODOLOGY

4.3.1. REGRESSION ANALYSIS

The relationship between idiosyncratic volatility and excess returns of pension funds is examined by using regression analysis. Following Angelidis (2010), idiosyncratic volatility is defined as the standard deviation of the regression residual ε_t from the regression function of CAPM. The single factor model equation is the following:

$$R_{it} - r_{ft} = \alpha + \beta(R_{mt} - r_{ft}) + \varepsilon_{it} \tag{4.1}$$

$i = 1, \dots, N; t = 1, \dots, N$

The dependent variable is the excess return of pension fund i. Where R_{it} is the weekly return of a pension fund, R_{mt} is the weekly return of the market portfolio proxy, r_{ft} is the effective weekly risk-free rate and ε_{it} is the regression residual.

The idiosyncratic volatility of pension fund i is measured as the following: (1) the weekly excess returns of pension fund i are regressed on the market premium $R_{mt} - r_{ft}$, (2) the regression residuals ε_{it} is extracted, and (3) the monthly standard deviation of regression residuals are calculated for pension fund i.

In order to examine whether idiosyncratic volatility is priced for Australian pension fund returns, CAPM is augmented by the idiosyncratic volatility. The regression equation takes the following form:

$$R_{it} - r_{ft} = \alpha + \beta(R_{mt} - r_{ft}) + iIdiovol_{it} + \varepsilon_{it} \tag{4.2}$$

Where R_{it} is monthly return of pension fund, R_{mt} is the monthly return of the market portfolio proxy, r_{ft} is the effective monthly risk-free rate and $Idiovol_{it}$ is the monthly idiosyncratic volatilities of the pension funds.

Regression equation (4.2) is the base model. In order to capture the variation of returns of different categories pension funds and test the robustness of the idiosyncratic volatility, a bond market factor is augmented to the regression model. A bond market factor will capture variation of returns for pension funds investing in bonds. The regression equation is as follows:

$$R_{it} - r_{ft} = \alpha + \beta(R_{mt} - r_{ft}) + \gamma(R_{bondt} - r_{ft}) + iIdiovol_{it} + \varepsilon_{it} \tag{4.3}$$

Where R_{it} is the monthly return of pension fund, R_{mt} is the monthly return of the market portfolio proxy, R_{bondt} is the monthly return of UBS Warburg bond index , r_{ft} is the effective monthly risk-free rate, $Idiovol_{it}$ is the monthly idiosyncratic volatilities of pension fund portfolio.

4.3.2. CONSTRUCTION OF THE PENSION FUND SIZE FACTOR AND THE IDIOSYNCRATIC VOLATILITY FACTOR

The idiosyncratic volatility effect on the returns of Australian pension funds is also tested by using the factor mimicking portfolio approach of Fama and French (1993). Following Fama and French (1993), an idiosyncratic volatility factor and a fund size factor are constructed. The idiosyncratic volatility factor is constructed as the returns of high idiosyncratic volatility portfolio minus the returns of low idiosyncratic volatility portfolio. The fund size factor is constructed as the returns of small size fund portfolio minus the returns of big size fund portfolio. More details in regard to construction of the idiosyncratic volatility portfolios and fund size portfolios are outlined in section **4.3.2.2.**.

4.3.2.1. REGRESSION ANALYSIS: THE FACTOR MIMICKING APPROACH

The pricing of the idiosyncratic volatility factor is examined by the following regression function:

$$R_{pt} - r_{ft} = \alpha + \beta(R_{mt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t \quad (4.4)$$

where R_{pt} is the equal-weighted monthly average return of the pension fund portfolios, R_{mt} monthly is the return on the market portfolio proxy, r_{ft} is the monthly risk-free rate, SMB is the return on the small pension fund portfolios minus the return of the large pension fund portfolios, $HIMLI$ is the return of the high idiosyncratic volatility pension fund portfolios minus the return of the low idiosyncratic volatility pension fund portfolios.

4.3.2.2. PORTFOLIO CONSTRUCTION

Pension funds are sorted into two portfolios, one small and one big, at the end of December of each year based on whether their size in December is bigger or smaller than the median fund size. The pension funds are then sorted into three idiosyncratic volatility portfolios (Low, Medium, High). Low idiosyncratic volatility portfolios contain 1/3 low idiosyncratic volatility pension funds, high idiosyncratic volatility portfolio contains 1/3 high idiosyncratic volatility pension funds, and the rest of 1/3 pension funds are medium pension funds.

4.3.2.3. THREE RISK FACTORS AND INTERSECTION PORTFOLIOS CONSTRUCTION

Three risk factors are formed as follows**:** (i) $R_{mt} - r_{ft}$ is the monthly return on the market portfolio proxy minus the monthly return of the risk free rate; (ii) SMB_t is the monthly return of small pension funds minus the monthly return of big pension funds, the size factor-SMB mimics the risk factor in returns associated with size. (iii) $HIMLI_t$ is the monthly return of high idiosyncratic volatility pension funds minus the monthly return of low idiosyncratic volatility pension funds. The idiosyncratic volatility factor HIMLI mimics the risk factor in returns associated with idiosyncratic volatility.

Six pension fund portfolios (H/B, H/S, M/B, M/S, L/B and L/S) are formed from the intersections of two size and three idiosyncratic volatility portfolios. For example, H/B portfolio contains high idiosyncratic volatility and big size pension funds. Monthly equally weighted returns of the six portfolios are calculated from January of year t to January of year t+1, and portfolios are rebalanced each year in January according to the size and idiosyncratic volatility of the pension funds in the previous December.

4.4. EMPIRICAL RESULTS

4.4.1. SUMMARY STATISTICS

Table 4.1 presents the summary statistics of monthly returns and idiosyncratic volatility of pension funds. Panel A shows the summary statistics of monthly returns of the pension funds. In Panel A, it is shown that equity pension funds generate a highest monthly return of 0.38% and fixed income pension funds generate a lowest monthly return of 0.33% over the sample period. Panel B shows the summary statistics of monthly idiosyncratic volatility of pooled pension funds and other pension fund categories. As idiosyncratic volatility measures the level of unsystematic risk, Table 4.1 shows the level of unsystematic risk in different pension fund portfolios. As expected, the idiosyncratic volatility of equity pension funds has the highest mean amongst all four groups. The reason for this is that equity pension funds invest heavily in the stock market, and since stocks are generally more volatile than bonds and real estate, this is not surprising. Idiosyncratic volatility of fixed-income pension funds has the lowest average return amongst all four groups. This is also expected since the return of fixed-income securities is far less volatile than the return of stocks. Idiosyncratic volatility of allocation pension funds is ranked between equity pension funds and fixed-income pension funds. Allocation pension funds invest in a variety of asset classes, such as stocks, bonds, real estate etc. Therefore, allocation pension should be less volatile than equity pension funds but more volatile than allocation pension funds. This is supported by the standard deviations in Table 4.1.

Table 4.1 Summary statistics: monthly fund returns and idiosyncratic volatilities of the pension funds from 1994 to 2008

Panel A: Fund Returns				
	Mean	**Maximum**	**Minimum**	**Std. Dev.**
Pooled Pension Funds	0.0038	0.0335	-0.0822	0.0176
Equity Pension Funds	0.0045	0.054	-0.1175	0.0276
Fixed Income Pension Funds	0.0033	0.0135	-0.0078	0.0031
Allocation Pension Funds	0.0039	0.0326	-0.0628	0.0158
Panel B: Idiosyncratic volatility				
	Mean	**Maximum**	**Minimum**	
Pooled Pension Funds	0.0156	0.0479	0.0073	
Equity Pension Funds	0.0264	0.0789	0.0127	
Fixed Income Pension Funds	0.0042	0.012	0.0016	
Allocation Pension Funds	0.0118	0.027	0.0049	

4.4.2. REGRESSION RESULTS

The pooled pension fund portfolios consist of equity pension funds, fixed income pension funds and allocation pension funds. As each category invests in different class of assets, each category of pension funds is tested individually in the following sections. The purpose is to distinguish characterises of different pension funds category. This section reports the results of the regression analysis. First, regression results of the pooled pension funds are presented. Second, the full sample is sorted into equity pension funds, fixed-income pension funds and allocation pension funds according to Morningstar's broad categories. The regression results are then reported separately for each portfolio of pension funds.

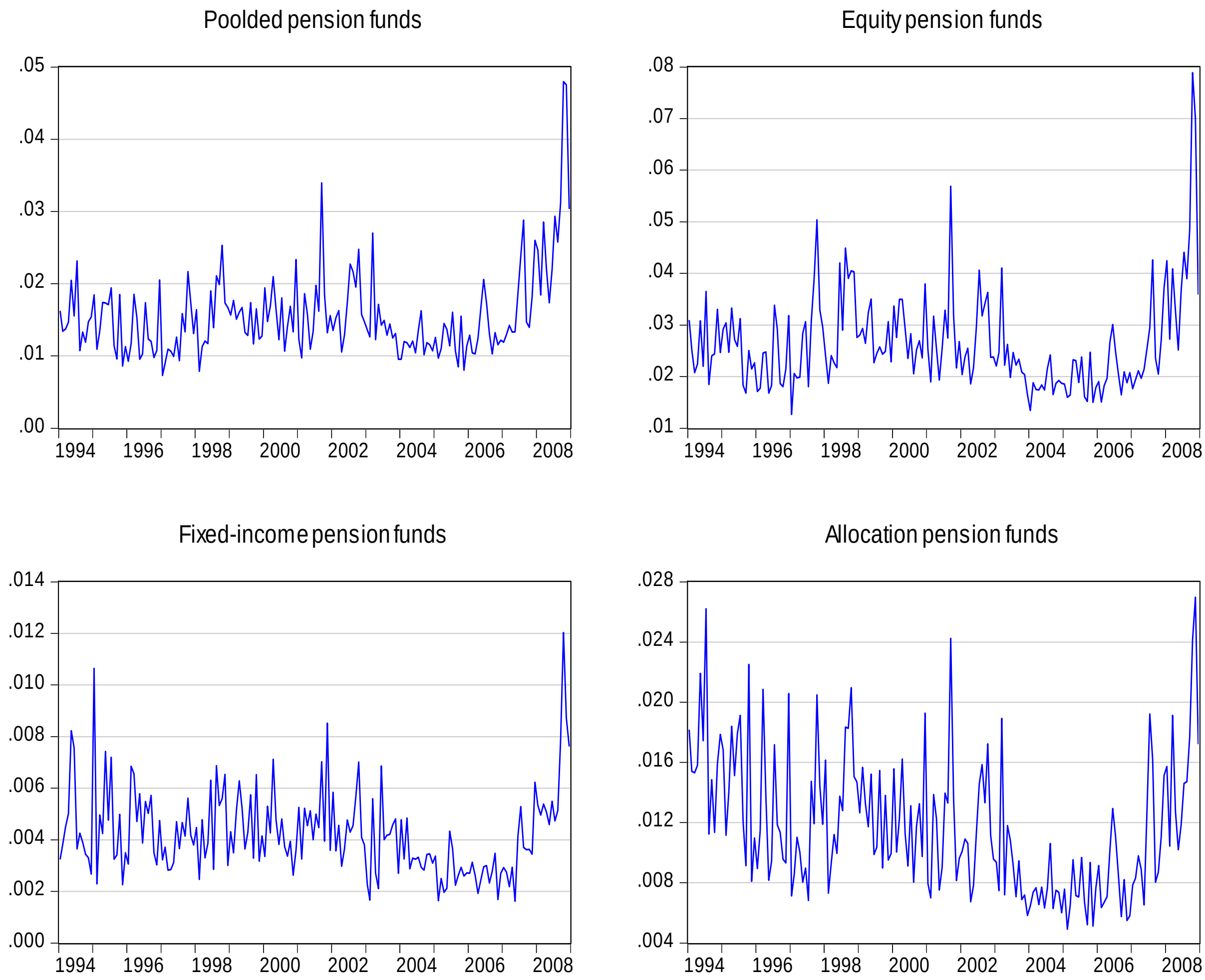
Figure 4.3 shows the historical monthly equally-weighted idiosyncratic volatility of pooled pension funds, equity pension funds, fixed-income pension funds and allocation pension funds from 1994 to 2008. The patterns of idiosyncratic volatilities demonstrate cyclical movements over the sample period.

The idiosyncratic volatility of pooled pension funds was low between 1994 and 2000 and high between 2001 and 2002; idiosyncratic volatility was low again from 2002 to 2007 then increased dramatically from mid-2008. This is consistent with Ooi et al. (2009), they find idiosyncratic volatility increases dramatically during economic downturn but decreases marginally during economic boom.

The pattern of idiosyncratic volatility of the equity pension funds group shows a similar cyclical movement as the pooled pension funds over the sample period, although the idiosyncratic volatility mean of equity pension funds is the highest amongst all four pension fund groups.

The idiosyncratic volatility of fixed-income pension funds shows cyclical movement over the sample period but the average of idiosyncratic volatility is the lowest amongst the four groups. Idiosyncratic volatility was high in 1994 followed by a drift from 1995 to 2001. Idiosyncratic volatility was high again in 2001, drifting again from 2002 to 2007 and the increasing dramatically in 2008.

Figure 4.3 Time series of monthly average idiosyncratic volatilities of pooled pension funds, equity pension funds, fixed-income pension funds and allocation pension funds from 01/1994 to 12/2008



Idiosyncratic volatility of allocation pension funds was high from 1994 to 2002. Then it entered a low idiosyncratic volatility period from 2003 to 2007, and again it increased dramatically in 2008.

All four groups of pension funds show a similar pattern in their idiosyncratic volatility. This indicates that changes in economic conditions could have significant impact to idiosyncratic volatility.

4.4.2.1. POOLED PENSION FUNDS

The regression results of the pooled pension funds group are summarized in Table 4.2. In Table 4.2, all the market premium coefficients are positive and significant at the 1% level. This is expected because it indicates that the market premium explains the excess return of pension funds from 1994 to 2008. All four coefficients have positive signs which indicate the market premium is positive related to the excess return of pension funds. The idiosyncratic volatility coefficients are significant at the 1% level but they have negative signs. Further, by adding idiosyncratic volatility into the model, the Adjusted R-squared only increased by 1%. This implies that idiosyncratic volatility is statistically significant in explaining the excess returns of the pooled pension funds but it lacks of economic meaning.

The R-squared values for each of the models that included market premium as an explanatory variable is over 80%. Following the exclusion of the market premium in Model 3, the R-squared is reduced to 30%. This suggests that even idiosyncratic volatility does help explain the variation in excess returns of pension funds, but the market premium explains a larger proportion of the variation in the excess return of pension funds.

Table 4.2 Regression results: pooled pensions funds

Model	α	β	i	R^2
1	-0.0018***	0.4372***		86%
t-stat	-3.55	-32.55		
2	0.0046***	0.4061***	-0.4038***	87%
t-stat	-3.03	-27.9	-4.45	
3	0.0241***		-1.6159***	30%
t-stat	-7.77		-8.73	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4.3 Regression results: equity pensions funds

Model	α	β	i	R^2
1	-0.0015**	0.6894***		87%
t-stat	-1.99	-34.77		
2	0.0050**	0.6615***	-0.2453***	88%
t-stat	-2.07	-30.29	-2.81	
3	0.0375***		-1.4376***	24%
t-stat	-6.9		-7.41	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.2.2. EQUITY PENSION FUNDS

The regression results of the equity pension funds group are summarized in Table 4.3. All the market premium coefficients are positive and significant at 1% level. This indicates that the market premium explains the excess return of equity pension funds from 1994 to 2008. The coefficients of the idiosyncratic volatility are significant at the 1% level for Model 2 and Model 3, and all these coefficients have negative signs. This indicates that contemporaneous idiosyncratic volatility is negatively related to the excess return of pension funds from 1994 to 2008. Idiosyncratic volatility is statistically significant in pricing the excess returns of equity pension funds.

The R-squared values are above 80% for the models that included the market premium variable. Following the exclusion of the market premium variable in Model 3, the R-squared reduces to 24%. This suggests that idiosyncratic volatility does help explain the variation in excess return of equity pension funds, although the market premium explains a larger proportion of variation in the excess returns of equity pension funds.

4.4.2.3. FIXED-INCOME PENSION FUNDS

The regression results of the fixed-income pension funds group are summarized in Table 4.4. A bond factor is included in the regression equations (see equation (4.3)). The purpose for introducing this bond factor into the regression model is because the stock market factor is unlikely to capture much variation in fixed-income pension funds returns. A bond market factor, on the other hand, may capture the proportion of variation of fixed income pension funds return missed by the stock market factor.

In Table 4.4, each of the stock market premium coefficients are positive and significant at the 1% level suggesting the stock market premium does help to explain the excess return of fixed-income pension funds from 1994 to 2008. The coefficients of idiosyncratic volatility are significant at the 1% level but all have negative signs. Again, the results indicate that the idiosyncratic volatility is statistically significant but lacks economic meaning in explaining the excess returns of the fixed-income pension funds as there is little change in the adjusted R-squared value.

Model 4 of Table 4.4 shows the regression results when a bond factor is presented in the regression model. The coefficient of the bond factor is positive and significant at 1% level. The R-squared values are between 9% and 15% for the Models 1 to 3. However, the R-squared jumped to 75% once the bond factor was introduced as an explanatory variable. This indicates that the bond factor captures considerable variation in the excess return of fixed-income pension funds.

Table 4.4 Regression results: fixed-income pension funds

Model	α	β	γ	i	R^2
1	-0.0018***	0.0272***			11%
t-stat	-8.27	-4.77			
2	0.0007			-0.5546***	9%
t-stat	-1.1			-4.25	
3	-0.0002	0.0211***		-0.3735***	15%
t-stat	-0.26	-3.52		-2.75	
4	-0.0005	0.0161***	0.2128***	-0.3388***	75%
t-stat	-1.37	-4.9	-20.48	-4.58	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.2.4. ALLOCATION PENSION FUNDS

The regression results are summarized in Table 4.5. Each of the market premium coefficients are significant at the 1% level and have positive signs. This indicates that the market premium variable explains the excess return of allocation pension funds. The bond premium coefficients are significant and have positive signs in Model 4 and 5. The idiosyncratic volatility coefficient is significant and negative if the stock market premium and bond premium variables are absent, but it becomes insignificant when the stock market premium variable is introduced in the regression function. In Model 4, when both the stock market premium and the bond market premium variables are introduced, the coefficient of idiosyncratic volatility is significant at 10% level but the adjusted R-squared only increases by about 2% when compared to the results of Model 3. Further, the coefficients of idiosyncratic volatility have negative signs; this is consistent with other pension groups.

The R-squared values are observed to be above 88% if the market excess return variable is introduced regardless of whether the stock market excess return or bond market excess return or both are included in the model. However, if the market excess return is absent from the regression, R-squared drops to 17%. This indicates that the market factor captures much of variation in the excess return of pension funds, but idiosyncratic volatility doesn’t capture much variation in the excess return of pension funds.

Table 4.5 Regression results: allocation pension funds

Model	α	β	γ	i	R^2
1	-0.0016***	0.3971***			88%
t-stat	-3.97	-36.2			
2	0.0157***			-1.4210***	17%
t-stat	-5.2			-5.94	
3	-9.29E-06	0.3902***		-0.1371	88%
t-stat	-0.007	-32.43		-1.38	
4	0.0004	0.3838***	0.1674***	-0.1778*	89%
t-stat	-0.3	-33.52	-4.72	-1.89	
5	-0.0008	0.3927***	0.1678***		89%
t-stat	-0.71	-37.55	-4.63		

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.2.5. RESULT SUMMARY

Overall, the results show that idiosyncratic volatility is statistically significant in the pricing of Australian pension fund returns from 1994 to 2008 which support that idiosyncratic volatility proxy risk in returns. This provides motivation to undertake additional analysis using the mimicking portfolio approach of Fama and French (1993). The results are presented in the following section.

4.4.3. MIMICKING PORTFOLIO APPROACH OF FAMA AND FRENCH (1993)

This section presents the regression results of an analysis using the mimicking portfolio approach of Fama and French (1993). Following Fama and French (1993) and Drew et al. (2006), pension funds are sorted into six size and idiosyncratic volatility interactive portfolios and subsequently, risk mimicking factors are formed following the Fama-French mimicking risk factor approach.

4.4.3.1. POOLED PENSION FUNDS

In Table 4.6, the summary statistics of six pension fund portfolios formed on size and idiosyncratic volatility are presented. The summary statistics indicate that three small fund portfolios generate higher returns than the three big fund portfolios and high idiosyncratic volatility portfolios are more volatile than low idiosyncratic volatility portfolios.

Table 4.6 Summary statistics: pooled pension funds

Idiosyncratic volatility						
	low	**medium**	**high**	**low**	**medium**	**high**
size	mean			S.D.		
small	0.0037	0.0050	0.0043	0.0087	0.0180	0.0271
big	0.0036	0.0046	0.0033	0.0121	0.0209	0.0277

Table 4.7 presents regression coefficients of a three-factor model which consisting of a market factor, a fund size factor and an idiosyncratic volatility factor. All intercepts are significant at the 1% level, and they are all negative. As expected, all β s are significant and all show positive signs. Coefficients of the fund size factor are significant and positive for three small size fund portfolios. The coefficients of the idiosyncratic volatility factor HIMLI are all significant at the 1% level and they have positive signs. High idiosyncratic volatility portfolios tend to have bigger loadings suggesting that excess returns of high idiosyncratic volatility portfolios are more sensitive to changes in idiosyncratic volatility.

Table 4.7 Regression results: pooled pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0019***	-0.0011***	-0.0018***	0.1742***	0.3568***	0.2301***
t-stat	-5.47	-2.29	-4.39	9.47	14.31	11.08
big	-0.0020***	-0.0013***	-0.0022***	0.2349***	0.3656***	0.1934***
t-stat	-4.62	-2.43	-4.95	10.31	13.48	8.45
	s			h		
small	0.4904***	0.61***	0.9623***	0.1180***	0.302***	1.1420***
t-stat	4.56	4.18	7.92	3.31	6.26	28.41
big	0.0560	0.0398	-0.2677**	0.1430***	0.4009***	1.1322***
t-stat	0.42	0.25	-2.00	3.25	7.64	25.57
	R^2					
small	74%	89%	97%			
big	79%	90%	96%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

The average R-squared value is 87.5%, with the high idiosyncratic volatility portfolios having higher R-squared. This suggests that this model captures more variations in excess returns of high idiosyncratic volatility pension funds than excess returns of low idiosyncratic volatility pension funds.

Although the intercepts reported in Table 4.7 are statistically significant, Fama and French (1993) suggest that significant small intercepts and high average R-squared give the model a chance to explain the variation in the returns. In Table 4.7, the average intercept is -0.171% per month and the average R-squared is 87.5%. Therefore, these significant small intercepts and high R-squared values suggest that this three-factor model captures most of the variation in the excess returns of pooled pension fund portfolios.

4.4.3.2. EQUITY PENSION FUNDS

The summary statistics of six equity pension fund portfolios are presented in Table 4.8. These statistics indicate that high idiosyncratic volatility fund portfolios have low returns. This is consistent with the regression results from section 4.4.2.2. which suggest a negative relationship between excess returns and idiosyncratic volatility.

Table 4.8 Summary statistics: equity pension funds

Idiosyncratic volatility						
	low	**medium**	**high**	**low**	**medium**	**high**
size	mean			S.D.		
small	0.0067	0.0058	0.0036	0.0247	0.0058	0.0319
big	0.0068	0.0054	0.0016	0.0292	0.0279	0.0345

Table 4.9 shows the regression coefficients of a three-factor model. All six intercepts are insignificant which indicates the model explains the excess return of equity pension funds well since standard asset pricing models should have insignificant intercepts (Merton (1973)). All β coefficients are significant at the 1% level and do not vary much from an average of 0.73. This is consistent with Fama and French (1993, 1996) who find the coefficients of the market factor do not change much when moving across different portfolios. Excess returns of high idiosyncratic volatility portfolios are more sensitive to changes in the mimicking idiosyncratic volatility factor. The average R-squared is 90.56% which indicates that the model does capture much of variation in excess return of equity pension fund portfolio.

The results suggest that this three-factor model captures significant variations in the excess returns of equity pension funds. This is not surprising because the Fama and French factor mimicking approach is designed to capture the variation in returns of stock portfolios. Moreover, the mimicking idiosyncratic volatility factor does a very good job in capturing the variations in excess returns of equity pension fund portfolios because, as shown in the previous section, that idiosyncratic volatility is a pricing factor for equity pension fund portfolios.

Table 4.9 Regression results: equity pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0005	-0.0006	-0.0001	0.7031***	0.6953***	0.7740***
t-stat	-0.83	-0.73	-0.22	37.59	28.78	41.34
big	-0.0003	-0.0001	-0.0009	0.7939***	0.6966***	0.7322***
t-stat	-0.54	-0.14	-1.07	43.02	30.76	30.87
	s			h		
small	0.9998***	1.1212***	1.1168***	0.0035	0.2383***	0.9436***
t-stat	9.83	8.53	10.97	0.0876	4.68	23.92
big	0.3483***	0.0761	0.0561	-0.0073	0.2964***	1.0816***
t-stat	3.47	0.62	0.43	-0.19	6.21	21.64
	R^2					
small	90%	85%	94%			
big	93%	89%	92%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.3.3. FIXED-INCOME PENSION FUNDS

Table 4.10 presents the summary statistics for returns of fixed-income pension fund portfolios. The average mean return is the smallest among different categories of pension funds and the standard deviations of the six fixed-income portfolios are much lower than the standard deviation of the equity pension fund portfolios. Fixed-income pension funds invest heavily in fixed-income securities such as bonds, so fixed-income pension funds are not as risky as equity pension funds.

Table 4.10 Summary statistics: fixed-income pension funds

Idiosyncratic volatility						
	low	**medium**	**high**	**low**	**medium**	**high**
size	mean			S.D.		
small	0.0033	0.0030	0.0039	0.0010	0.0061	0.0075
big	0.0032	0.0027	0.0030	0.0008	0.0038	0.0082

Table 4.11 shows the regression results of a three-factor model. All six intercepts from the regressions are significant at the 1% level. This indicates that the three factor model does not explain all variations in the excess returns of fixed-income pension funds. Three out of six coefficients of the stock market factor are insignificant which suggests that stock market factor does not always work for fixed-income securities. SMB and HIMLI still capture the proportion of variation in excess returns missed by the market factor. Excess returns of high idiosyncratic portfolios are more sensitive than those of low idiosyncratic portfolios.

The average R-squared value is 46.43%. High idiosyncratic portfolios have a high R-squared (above 90%), but medium and low idiosyncratic volatility portfolios have a low R-squared (between 4% and 47%).

Overall, the results suggest that this three-factor model does not explain the variation in the excess returns of fixed income pension funds very well. As the fixed-income pension funds invest primarily in fixed income securities and the portfolio mimicking approach is primarily designed to explain stock returns, so this three-factor model developed by using the portfolio mimicking approach does not capture much of variation in the excess returns of low to medium idiosyncratic volatility fixed income pension funds. However, this model captures much of the variation in the excess returns of high idiosyncratic fixed income funds which supports the notion that idiosyncratic volatility is important in pricing fixed income pension funds.

Table 4.11 Regression results: fixed-income pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0017***	-0.0023***	-0.0018***	0.0051***	0.0308**	0.0026
t-stat	-26.48	-5.15	-20.01	2.66	2.37	1.01
big	-0.0018***	-0.0022***	-0.0018***	0.0021	0.0294***	0.0012
t-stat	-40.15	-9.80	-8.95	1.59	4.63	0.22
	s			h		
small	0.0564*	0.2226	0.3836***	-0.0213	0.2155**	0.8904***
t-stat	1.71	0.99	8.67	-1.51	2.24	47.30
big	-0.0279	-0.7692***	-0.8930***	0.0481***	0.4030***	1.3319***
t-stat	-1.21	-6.97	-8.92	4.90	8.58	31.99
	R^2					
small	4%	15%	98%			
big	23%	47%	91%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.3.4. ALLOCATION PENSION FUNDS

Allocation pension funds invest in a variety assets, such as stocks, bonds, real estate etc. It is supposed to be more diversified across asset classes than other categories of pension funds. Table 4.12 presents summary statistics of six allocation pension fund portfolios. In Table 4.12, there is no obvious pattern for the mean returns but the standard deviations tend to increase from low idiosyncratic volatility portfolios to high idiosyncratic volatility portfolios.

Table 4.12 Summary statistics allocation pension funds

Idiosyncratic volatility						
	low	**medium**	**high**	**low**	**medium**	**high**
size	mean			S.D.		
small	0.0044	0.0039	0.0047	0.0102	0.0159	0.0203
big	0.0046	0.0046	0.0045	0.0117	0.0182	0.0207

Table 4.13 presents the regression coefficients of a three-factor model. All six intercepts are significant and have negative signs. This indicates that the three-factor model does not capture all variations in excess return of allocation pension funds. All six β s are significant and have positive signs. This positive relationship between the market factor and excess returns of allocation pension funds is expected because allocation pension funds invest in stocks and the stock market factor is supposed to capture the proportion of variation in the excess returns of allocation pension funds. SMB and HIMLI capture the proportion of variation missed by the market factor. Again, excess returns of high idiosyncratic volatility portfolios are more sensitive to changes in HIMLI.

The R-squared values increase from low idiosyncratic volatility portfolios to high idiosyncratic volatility portfolios and the average R-squared is 88.62%. Consistent with the regression results presented in previous sections, this three-factor model captures greater variation for high idiosyncratic volatility portfolios. The regression results are similar to the regression results of pooled pension funds; both show small but significant intercepts and high R-squared values. Therefore, the model captures most of the variation in the excess returns of allocation pension fund portfolios.

Table 4.13 Regression results: allocation pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0011***	-0.0017***	-0.0009**	0.2298***	0.2302***	0.2410***
t-stat	-3.03	-4.10	-2.40	9.93	8.84	10.22
big	-0.0011***	-0.0013***	-0.0013***	0.2365***	0.2685***	0.2359***
t-stat	-2.95	-2.97	-3.19	10.51	10.28	9.74
	s			h		
small	0.0962	0.1234	0.3304**	0.0839	0.6948***	1.1581***
t-stat	0.63	0.72	2.12	1.10	8.11	14.91
big	-0.4823***	-0.6992***	-0.6900***	0.1025	0.6250***	1.0154***
t-stat	-3.24	-4.04	-4.30	1.38	7.26	12.73
	R^2					
small	79%	89%	94%			
big	84%	91%	94%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.4.3.5. THE BOND MARKET FACTOR

The regression results in the previous sections suggest that a three-factor model captures much variation in excess returns of equity pension funds, but the three-factor model does not explained much variation in excess returns for low idiosyncratic volatility fixed-income pension funds since the results produce significant regression intercepts and low R-squared values. The intercepts that are significant indicate that there is missing factor in the regression equation. Therefore, a bond market factor is included in the regression model because both fixed-income pension funds and allocation pension funds invest in bonds, so an additional bond market factor in the regression equation should improve the explanatory power of the model.

Table 4.14 shows the regression coefficients of monthly excess returns of six pooled pension fund portfolios of a four-factor model (see equation (4.3)). All intercepts are significant and have negative signs. This suggests that the model still leaves unexplained variation in the excess returns of pooled pension funds even when a bond market factor is included in the regression function. Overall, the inclusion of a bond market factor does not improve the explanatory power of the model for pooled pension funds.

Table 4.15 shows the regression coefficients of monthly excess returns of six fixed-income pension fund portfolios on the four factors. Table 4.15 shows that all intercepts are significant at the 1% level and R-squared values remain low for low idiosyncratic volatility portfolios. However, inclusion of the bond factor improves the R-squared for medium idiosyncratic volatility portfolio when compared to the results presented in Table 4.11. The inclusion of a bond market factor does not improve the explanatory power of the model for low and high idiosyncratic volatility fixed-income pension funds.

Table 4.16 shows the regression coefficients of monthly excess return of six allocation pension fund portfolios on the four factors. The intercepts, β , γ and h coefficients are significant at the 1% level. This indicate that model does not capture all the variation in the excess returns of allocation pension fund portfolio, but the inclusion of a bond market factor improves the explanatory power of HIMLI as the coefficients of HIMLI for low idiosyncratic volatility portfolios become significant at the 1% level. The R-squared values have improved for all six allocation pension fund portfolios, in particular the R-squared has increased by 11% for the low idiosyncratic volatility and small allocation pensions funds. To some extent, the inclusion of a bond market factor improves the explanatory power of the model for allocation pension funds compared to that of that three-factor model in section 4.4.3.4.

Table 4.14 Regression results: pooled pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \gamma(r_{bondt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0021***	-0.0013**	-0.0018***	0.1714***	0.3505***	0.2297***
t-stat	-6.10	-2.91	-4.53	9.56	14.52	10.98
big	-0.0021***	-0.0014**	-0.0024***	0.2351***	0.3638***	0.1899***
t-stat	-4.75	-2.67	-5.55	10.26	13.38	8.50
	γ			s		
small	0.0899**	0.1568***	0.0286	0.4536***	0.5359***	0.9541***
t-stat	2.68	3.47	0.73	4.27	3.75	7.71
big	0.0224	0.0642	0.1102**	0.0533	0.0149	-0.3130**
t-stat	0.52	1.26	2.63	0.39	0.09	-2.37
	h					
small	0.1266***	0.3155***	1.1453***			
t-stat	3.66	6.78	28.40			
big	0.1462***	0.4074***	1.1428***			
t-stat	3.31	7.77	26.51			
	R^2					
small	76%	90%	97%			
big	80%	90%	96%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4.15 Regression results: fixed-income pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \gamma(r_{bondt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0017***	-0.0020***	-0.0018***	0.0051***	0.0319***	0.00250
t-stat	-26.17	-4.88	-20.15	2.66	2.64	0.98
big	-0.0019***	-0.0020***	-0.0018***	0.0021	0.0299***	0.0014
t-stat	-40.70	-9.82	-8.92	1.57	5.04	0.24
	γ			s		
small	-0.0071	-0.5241***	0.0337	0.0621*	0.6426***	0.3566***
t-stat	-0.45	-5.26	1.61	1.75	2.87	7.56
big	0.0257**	-0.2466***	0.0264	-0.0485**	-0.5716***	-0.9123***
t-stat	2.37)	-5.03	0.48	-1.99	-5.19	-8.45
	h					
small	-0.0140	0.7487***	0.8561***			
t-stat	-0.66	5.54	30.16			
big	0.0220	0.6538	1.3051***			
t-stat	1.50	0.85	18.79			
	R^2					
small	5%	28%	98%			
big	25%	54%	91%			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4.16 Regression results: allocation pension funds

$$r_{pt} - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \gamma(r_{bondt} - r_{ft}) + sSMB_t + hHIMLI_t + \varepsilon_t$$

Idiosyncratic volatility						
size	**low**	**medium**	**high**	**low**	**medium**	**high**
	α			β		
small	-0.0015***	-0.0021***	-0.0013***	0.1478***	0.1579***	0.1607***
t-stat	-6.08	-6.03	-4.87	8.84	6.94	9.02
big	-0.0014***	-0.0016***	-0.0016***	0.1674***	0.1914***	0.1621***
t-stat	-5.04	-4.90	-5.32	9.03	8.67	8.08
	γ			s		
small	0.3724***	0.3281***	0.3643***	-0.0163	0.0243	0.2204**
t-stat	13.97	9.04	12.81	-0.16	0.17	1.99
big	0.3137***	0.3502***	0.3352***	-0.5770***	-0.8050***	-0.7912***
t-stat	10.61	9.95	10.48	-5.01	-5.87	-6.35
	h					
small	0.3902***	0.9647***	1.4577***			
t-stat	6.96	12.65	24.39			
big	0.3605***	0.9130***	1.2911***			
t-stat	5.80	12.34	19.21			
	R^2					
small	0.90	0.93	0.97			
big	0.91	0.95	0.97			

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

4.5. CONCLUSION

Idiosyncratic volatility is important in the pricing of pension funds. In this chapter, multi-factor models are employed to examine the importance of idiosyncratic volatility in the pricing of Australian pension funds. This chapter provides strong evidence that idiosyncratic volatility is priced for Australian Pension Funds from 1994 to 2008. More importantly, a three-factor model is based on the market risk factor, pension fund size factor and idiosyncratic volatility factor which exhibits strong explanatory power for the returns of equity pension funds. The implication of these findings is that investors should consider idiosyncratic volatility when evaluating the performance of funds, for example, investors should compare performance of the funds to a benchmark portfolio with matched idiosyncratic volatility.

This three-factor model captures a large amount of variation in excess returns of equity pension fund portfolios, but it lacks of power to explain the excess returns of fixed-income pension funds. A possible explanation is that the Fama and French factor mimicking approach is designed for stocks and different types of asset behave differently. Therefore, it is not surprising that the three-factor model does not capture all variation in returns for funds that invest in fixed-income securities.

The regression results show a negative relationship between the excess return of pension funds and idiosyncratic volatility. This negative relationship is hard to explain through rational finance theory, but a negative relationship between idiosyncratic volatility and returns has been documented in the literature, for example, Ang et al. (2006, 2009). This is indeed a puzzle, since idiosyncratic volatility should positively relate to excess return according to asset pricing theories. This study leaves this question to future research in this area.

CHAPTER 5

5. DO STOCK FUNDAMENTALS EXPLAIN IDIOSYNCRATIC VOLATILITY?

5.1. INTRODUCTION

The number of studies investigating idiosyncratic volatility has been growing rapidly since the late 1990's. The majority of these studies have focused on the pricing of idiosyncratic volatility for stock returns as opposed to investigating what factors explain idiosyncratic volatility. The purpose of this chapter is to explore the roles of stock fundamental ratios in explaining idiosyncratic volatility in the Australia stock market from 1993 to 2010. As idiosyncratic volatility is firm specific risk and stock fundamental ratios are proxies for firm specific information, idiosyncratic volatility should relate to stock fundamental ratios. This chapter explores the cross-sectional relationships between idiosyncratic volatility and the stock fundamental ratios.

Chapter 3 of this thesis shows that idiosyncratic volatility increases significantly during bad market times but decreases marginally during good market times from 1993 to 2010 in Australia. In this chapter, the empirical results show that there is an upward trend in the aggregate idiosyncratic volatility from 1993 to 2010 in Australia. As shown by Campbell, Lettau, Malkiel and Xu (2001), idiosyncratic volatility increased from 1962 to 1997 in the US. They suggest that investors should consider increasing the number of stocks in their portfolios over time in order to maintain the same level of diversification during their investment period. This has important implications for portfolio diversification. Therefore, further research is desirable to understand the driving factors of idiosyncratic volatility over time. Moreover, the Australian stock market is an important global market. Having grown at a rapid rate over the past few decades, it was the eighth largest equity market in the world (by market capitalisation) as at 31 August 2012[12]. However, previous studies in the area have concentrated on US and Japanese stocks and therefore this study is motivated to explore driving factors for idiosyncratic volatility in one of the most important equity markets in the world.

Previous studies have shown that profitability ratios (e.g. ROE and ROA), institutional ownership, future earnings growth rates, firm age and newly listing of riskier companies drive idiosyncratic volatility. For example, Malkiel and Xu (2003) find that future earnings growth rates of US listed companies were positively related to idiosyncratic volatility from 1986 to 1995. Chang and Dong (2006) find that institutional ownership and profitability ratios explain market aggregate idiosyncratic volatility from 1975 to 2003 by using Japanese stock market data. Using US data, Brown and Kapadia (2007) find that idiosyncratic volatility is driven by new listings of riskier companies from 1963 to 2002. Cao, Simin and Zhao (2008) find that corporate growth options explain idiosyncratic volatility in the US. These studies find that the driving factors of idiosyncratic volatility are proxies of firm specific information. As stock fundamental ratios proxy firm specific information, so this study is motivated by the hypothesis that stock fundamental ratios explain idiosyncratic volatility. The relationships between idiosyncratic volatility and firm specific information in the form of stock fundamental ratios, such as dividend yield,

[12] According to MSCI global index, http://www.asxgroup.com.au/the-australian-market.htm

earnings per share (hereafter EPS), ROE, interest cover ratio (hereafter Icover) and price to earnings ratio (hereafter PE), are examined.

In this chapter, portfolio analysis is also employed to determine the relationship between the stock fundamental ratios and idiosyncratic volatility. The stocks are sorted into portfolios according to size and idiosyncratic volatility. The results show that, for the size portfolios, big companies by size tend to have low idiosyncratic volatility, high Icover, high ROE, high EPS, high PE and vice-versa. As size and idiosyncratic volatility negatively correlated, similar results are obtained by using the idiosyncratic volatility portfolios. In general, the portfolio analysis results can be summarized as high idiosyncratic volatility companies are small by size, have low ability to meet debt obligation (measured by Icover), have low management performances (measured by ROE) and low profitability (measured by EPS), and investors are willing to pay less for every dollar of earnings (measured by PE).

The portfolio analysis suggests that some of the stock fundamental ratios are correlated with idiosyncratic volatility. Regression analysis is also employed to examine whether there are significant cross-sectional relationships between the stock fundamental ratios and idiosyncratic volatility. A panel regression model[13] with fixed effect is applied to control for the characteristics of the companies in the sample by capturing the firm specific effects. The regression results show a significant positive cross-sectional relationship between dividend yield and the idiosyncratic volatility. The regression results also show that other stock fundamental ratios explain idiosyncratic volatility. Size, ROE and PE are negatively related to the idiosyncratic volatility. These negative relationships suggest that

[13] Results of the Hausman test also indicate that a fixed effect model is preferred to a random effect model. The results will be available upon request.

high (low) idiosyncratic volatility stocks exhibit the following characteristics: small (big) by size, less (more) profitable by ROE and low (high) valued by PE.

The empirical results also show that the dividend yield, ROE and PE explain idiosyncratic volatility even in the presence of firm size. The results suggest that firm specific information explains aggregate idiosyncratic volatility in the Australia stock market from 1993 to 2002.

The reminder of this chapter is organized as follows. Section 5.2 describes the data. The methodology employed in this chapter is found in section 5.3. Section 5.4 presents the empirical test results. Finally, section 5 provides the conclusion.

5.2. DATA

Australian stock return, company size, book-to-market equity ratio, dividend yield, Icover, PE, ROE and EPS are downloaded from Datastream. The 90-day Australian Bank Accepted Bill Rate is sourced from the Reserve Bank of Australia website and employed as a proxy for the risk free rate in Australia. Total return indices of the stocks are used to calculate the returns of the stocks and ASX All Ordinaries Total Return Index to represent the market portfolio. The initial sample included all the active and dead ASX listed companies available on Datastream from 1993 to 2010.

For stock returns, daily data is downloaded. For size and BE/ME, monthly data is downloaded. For stock fundamental ratios, yearly data is downloaded. The thinly traded stocks are removed from the initial sample because Guant (2004) suggest that thinly traded and delisted stocks may show constant returns in post portfolio formation periods which lead to lower statistical reliability. Following Guant (2004), (1) stocks are required to have had at least one trade in a month, and (2) stocks are required to have had return, size measured by market capitalization and BE/ME at the same point in time. The top and bottom five precent observations for the stock fundamental ratios are also removed, because there are some significant outliers for these ratios. After cleaning the initial sample, there are 2034 companies in the final sample cross-sectionally.

Table 5.1 summarizes yearly averages of the variables from 1993 to 2010. Company sizes are scaled by taking the natural logarithm. In Table 5.1, there are no clear trends across time in relation to dividend yield, size, and EPS. However, there are some observable trends in idiosyncratic volatility, Icover, PE and ROE. Idiosyncratic volatility tends to increase over the sample period, but Icover, PE and ROE tend to decrease.

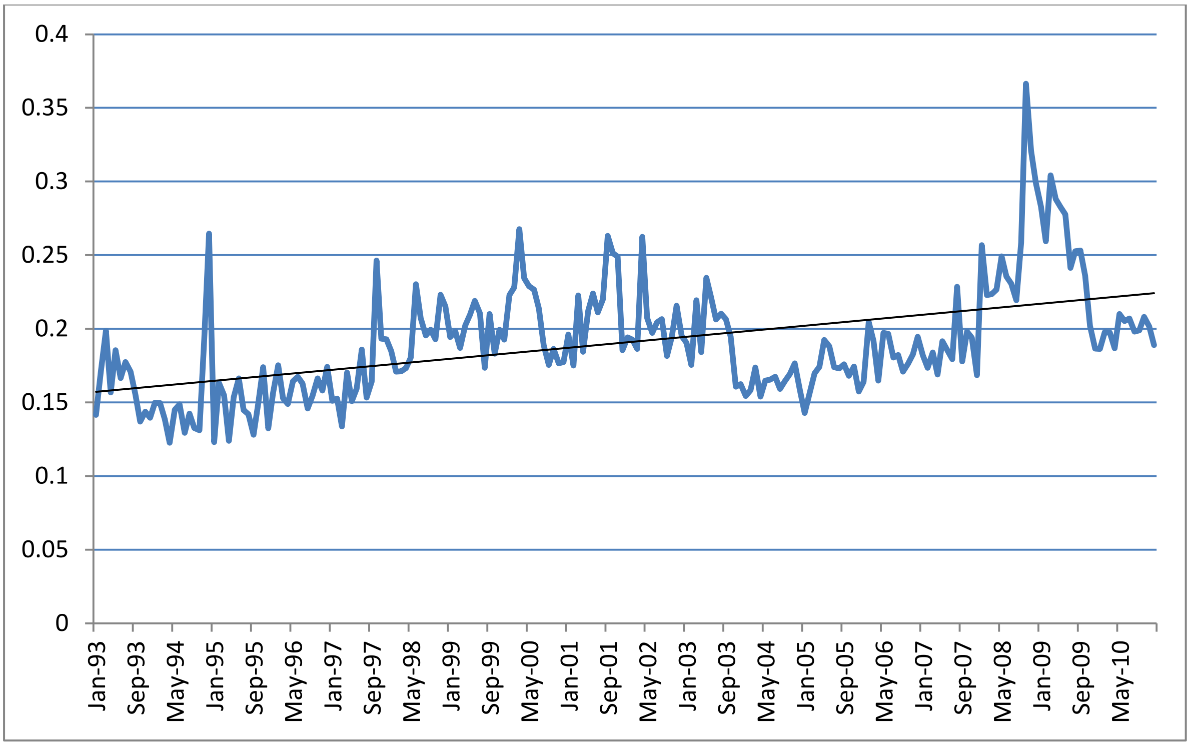
Table 5.1 Yearly averages of the variables

Year	Idiovol	dividend yield	Icover	size	PE	ROE	EPS
1993	0.0327	0.0378	4.51	1.55	6.93	0.0246	0.1406
1994	0.0306	0.0470	4.85	1.79	7.54	0.0644	0.1657
1995	0.0307	0.0513	6.38	1.70	6.61	0.0726	0.1553
1996	0.0346	0.0467	1.74	1.72	8.06	0.0773	0.1355
1997	0.0383	0.0472	-1.14	1.57	6.86	0.0412	0.1313
1998	0.0412	0.0514	-7.18	1.47	4.35	0.0090	0.1304
1999	0.0418	0.0494	-13.93	1.42	1.35	-0.0467	0.1324
2000	0.0452	0.0523	-29.84	1.60	-0.66	-0.0696	0.1480
2001	0.0458	0.0470	-36.43	1.49	-1.53	-0.1799	0.1079
2002	0.0429	0.0480	-36.15	1.42	-1.41	-0.1882	0.1233
2003	0.0407	0.0424	-29.35	1.39	-2.05	-0.1828	0.1188
2004	0.0358	0.0406	-30.48	1.56	-2.63	-0.1356	0.1479
2005	0.0369	0.0448	-27.89	1.61	-2.39	-0.1529	0.1482
2006	0.0393	0.0423	-30.26	1.63	-3.32	-0.1261	0.1636
2007	0.0414	0.0433	-32.92	1.75	-4.06	-0.1342	0.1693
2008	0.0550	0.0678	-36.43	1.78	-2.07	-0.1684	0.1612
2009	0.0518	0.0466	-30.64	1.33	-4.38	-0.2584	0.1238
2010	0.0419	0.0486	-20.88	1.61	-4.11	-0.1752	0.1583

Note. Idiovol is idiosyncratic volatility, Icover is interest cover ratio, PE is price-to-earnings ratio, ROE is return on equity, and EPS is earnings per share.

Figure 5.1 plots the yearly idiosyncratic volatility from 1993 to 2010. Overall, there is upward trend in idiosyncratic volatility over the sample period. This suggests that the idiosyncratic volatility increased from 1993 to 2010. This increase in idiosyncratic volatility may suggest that investors need to increase the number of stocks in their portfolios in order to maintain the desired level of diversification for their portfolios (see Campbell et al., 2001).

Figure 5.1 Time series of monthly average of idiosyncratic volatility from January 1993 to December 2010



5.3. METHODOLOGY

5.3.1. IDIOSYNCRATIC VOLATILITY ESTIMATION

Idiosyncratic volatility is not observable. Following Ang et al. (2006, 2009), idiosyncratic volatility is defined as the standard deviation of regression residuals of the Fama and French (1993) three-factor model. Therefore, the first stage for this step is to construct size and BE/ME portfolios by using daily stock returns. Companies are divided into total six portfolios in two steps. First, companies are divided into two size portfolios then each size portfolio is divided into three BE/ME portfolios. The two size portfolios consist of (i) the top 50% of companies (big) by market capitalization, and (ii) the bottom 50% companies (small) by market capitalization. The three BE/ME portfolios consist of (i) 1/3 high book-to-market equity ratio companies, (ii) 1/3 medium book-to-market equity ratio companies, and (iii) 1/3 low book-to-market equity ratio companies. Every year t, the companies are ranked and sorted into portfolios according to their size and BE/ME at December of year t-1. The return of the daily size portfolio is calculated as the daily returns of the big size portfolio minus the daily returns of the small size portfolio. The return of daily book to market equity portfolios is calculated as the daily returns of the high book-to-market equity ratio portfolio minus the daily returns of the low book-to-market equity ratio portfolio. The portfolios are rebalanced on an annual basis. Then, daily excess return of stock is regressed on the market factor, size factor and BE/ME factor. The regression equation is the following:

$$r_t - r_{ft} = \alpha + \beta(r_{mt} - r_{ft}) + \lambda SMB_t + \delta HML_t + \varepsilon_t \tag{5.1}$$

$$\varepsilon_t \sim N(0, \sigma^2), t = 1, \dots, t$$

Where r_t is the daily returns of stock i, r_{ft} is the daily 90-day bank acceptable bill rate, r_{mt} is the daily returns of S&P/ASX All Ordinary Index, SMB_t and HML_t are the daily returns of the size portfolio and book-to-market equity portfolio respectively. Yearly idiosyncratic volatility is estimated as the yearly standard deviation of regression residual ε_t from regressing equation (5.1).

5.3.2. PORTFOLIO ANALYSIS

The relationship between the variables is first explored at the portfolio level. The stocks are sorted into five equally weighted portfolios according to size and idiosyncratic volatility to reveal the changes in the averages of other firm specific variables across the portfolios.

5.3.3. REGRESSION ANALYSIS

To estimate the cross-sectional relationship between the idiosyncratic volatility and stock fundamentals, the following regression, where idiosyncratic volatility is the dependent variable, is estimated:

$$Idiovol_{i,t} = \alpha_0 + a_1 DividendYield_{i,t} + a_2 I\,\mathrm{cov}er_{i,t} + a_3 Size_{i,t} + a_4 PE_{i,t} + a_5 ROE_{i,t} + a_6 EPS_{i,t} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma^2), t = 1, \ldots . n; i = 1, \ldots . n \tag{5.2}$$

Where $Idiovol_{i,t}$, $DividendYield_{i,t}$, $I\,\mathrm{cov}er_{i,t}$, $Size_{i,t}$, $PE_{i,t}$, $ROE_{i,t}$, $EPS_{i,t}$ are the idiosyncratic volatility, dividend yield, interest cover ratio, size[14], price to earnings ratio, ROE and earnings per share of company i at year t.

A panel data model with fixed effects is employed to control the effects of independent variables that vary over time. The rationale is that a company’s earnings is not constant over time, and changes in those earnings have a direct impact on the independent

[14] Size is scaled by taking natural logarithm.

variables and the dependent variables. Hence, if a company's earnings is not a constant over time, then any changes in the earnings should lead to changes in the variables such as Icover, PE, dividend yield etc. Consequently, a fixed effect model is employed to control for the effects the variables. Moreover, the Hausman test is employed to determine whether fixed effect model or random effect is more suitable. The results of this test strongly support the use of fixed effect in the regressions[15].

5.4. EMPIRICAL RESULTS

5.4.1. PORTFOLIO ANALYSIS

Table 5.2 presents the average idiosyncratic volatility, dividend yield, Icover, ROE, EPS and PE of five size sorted portfolios. Portfolio 1 comprises the biggest companies by market capitalization and portfolio 5 comprises the smallest companies by market capitalization.

In Table 5.2, the yearly variables are ranked by size and sorted into five portfolios with an equal number of stocks in each portfolio. The statistics in Table 5.2 suggest patterns are evident in idiosyncratic volatility, Icover, ROE, EPS and PE when moving from portfolio 1 to portfolio 5. The patterns are shown in Figure 5.2 to Figure 5.7. Figure 5.2 indicates that idiosyncratic volatility increases when moving from portfolio 1 to portfolio 5. This suggests that big companies tend to have low idiosyncratic volatilities and this finding is consistent with the findings reported in Chapter 3 of this thesis, as well as of previous studies, example Bali et al (2005) find that small companies have high idiosyncratic

[15] The results of the Hausman test are available upon request.

volatility in the US. The empirical results in Chapter 3 suggest the same relationship between the size of companies and their idiosyncratic volatilities in Australia.

In Figure 5.3, there isn't a monotonic pattern in the dividend yield when moving from portfolio 1 to portfolio 5. However, there is a bell shaped distribution in dividend yields when companies are sorted by size. It is shown that the average dividend yield increases when moving from portfolio 1 to portfolio 3 then it decreases when moving from portfolio 3 to portfolio 5 which suggest medium size companies pay higher dividends than the biggest and smallest companies in Australia.

In Figure 5.4, Icover decreases when moving from portfolio 1 to portfolio 4 then increases slightly when moving from portfolio 4 to portfolio 5. This suggests that big companies have a high interest cover ratio as big companies have a better ability to meet debt obligations by using profits than do small companies. The average Icover for portfolio 1 is 4.4089 which indicates that big companies tend to have lower leverages than small companies.

Figure 5.5 shows a decreasing pattern in the average ROE when moving from portfolio 1 to portfolio 5. This indicates that big companies tend to use equity capital in a more effective way to generate profit than small companies. ROE also measures management performance. Therefore, in addition, the results suggest that big companies have better management performance than small companies.

Figure 5.6 shows that EPS decreases when moving from portfolio 1 to portfolio 5. This pattern suggests that big companies are more profitable than small companies. Figure 5.7 shows a decreasing pattern for PE when moving from portfolio 1 to portfolio 5. This decreasing pattern suggests that big companies have high PE ratios. Portfolios 1 and 2 have positive PE ratios and Portfolios 3 to 5 have negative PE ratios suggesting that big companies tend to have positive earnings but small companies may have negative earnings over the sample period.

Table 5.2 Equally weighted average of the variables in five size sorted portfolios

Portfolios sorted by company size					
	1 (Biggest)	**2**	**3**	**4**	**5 (smallest)**
Idiovol	0.0197	0.0295	0.0418	0.0501	0.0505
Dividend Yield	0.0402	0.0456	0.0482	0.0459	0.0357
Interest Cover Ratio	4.4089	-5.3013	-13.9958	-21.4573	-21.1850
Return of Equity	0.0719	-0.0022	-0.1241	-0.2472	-0.3547
EPS	0.1943	0.0894	0.0431	0.0223	0.0117
PE Ratio	7.9296	2.0905	-2.3890	-4.4693	-4.5311

Note. Size is scaled by taking natural logarithm, other variables are the levels. Idiovol is idiosyncratic volatility, Icover is interest cover ratio, PE is price-to-earnings ratio, ROE is ROE, and EPS is earnings per share.

Figure 5.2 Average idiosyncratic volatilities of five size sorted portfolios

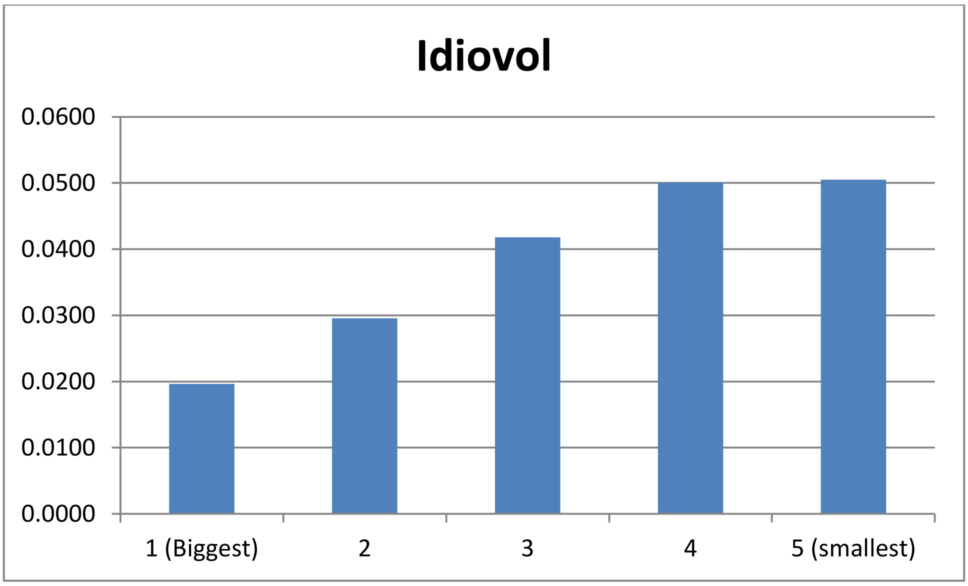


Figure 5.3 Average Dividend Yields of five size sorted portfolios

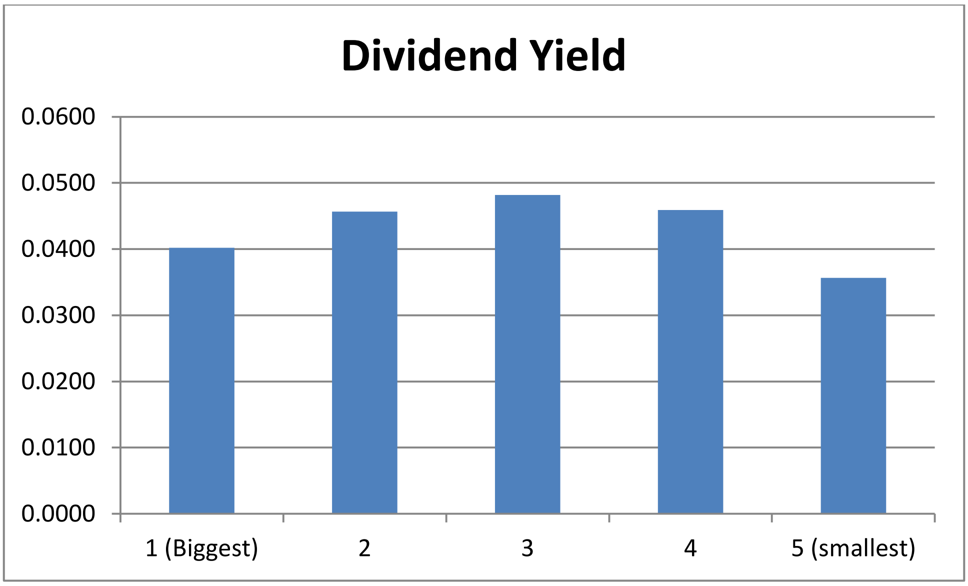


Figure 5.4 Average Interest Cover Ratios of five size sorted portfolios

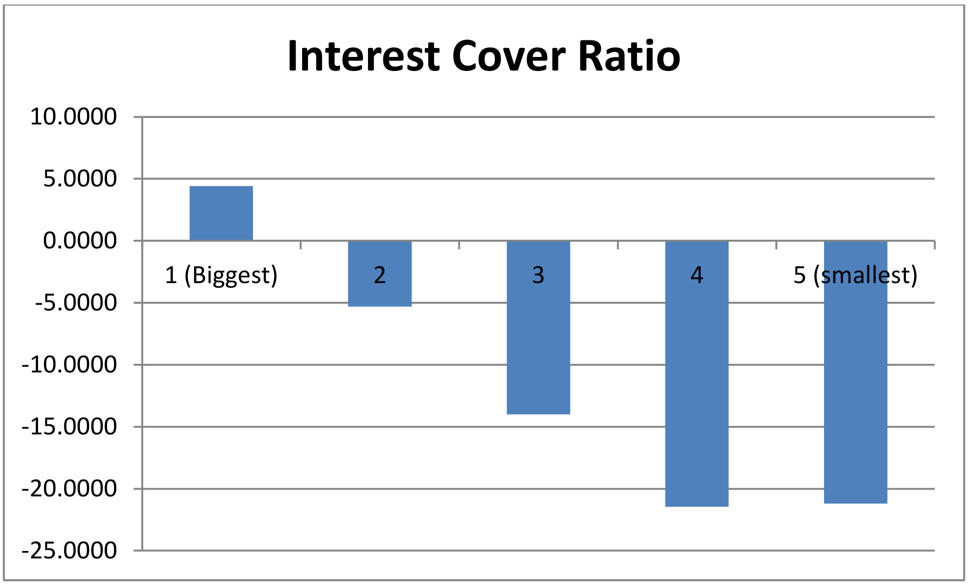


Figure 5.5 Average Return of Equity ratios of five size sorted portfolios

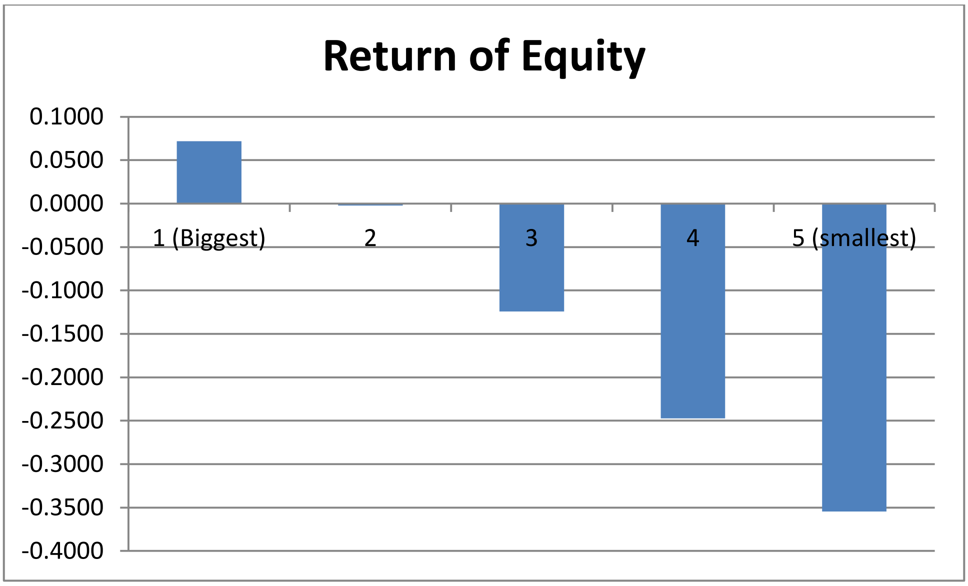


Figure 5.6 Average Earnings Per Share ratios of five size sorted portfolios

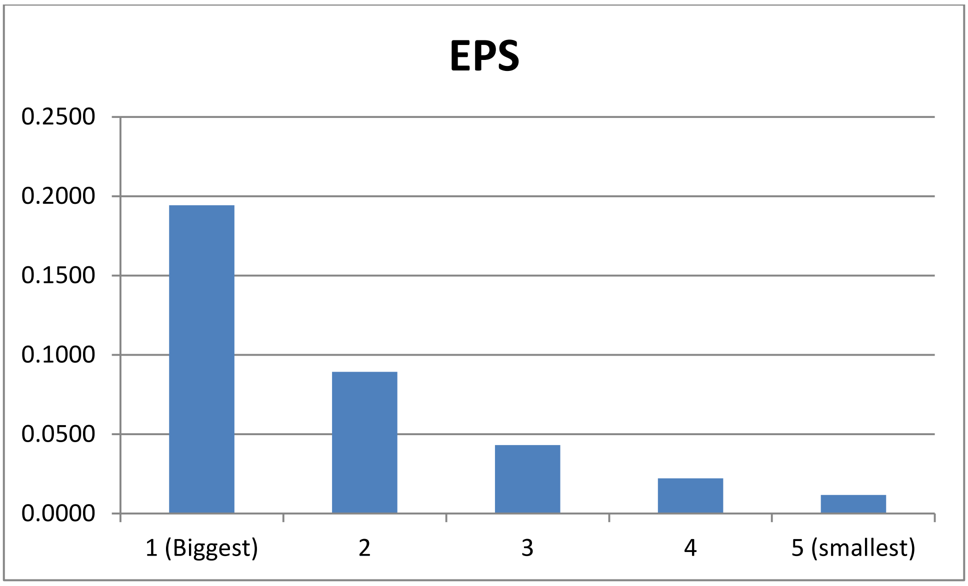
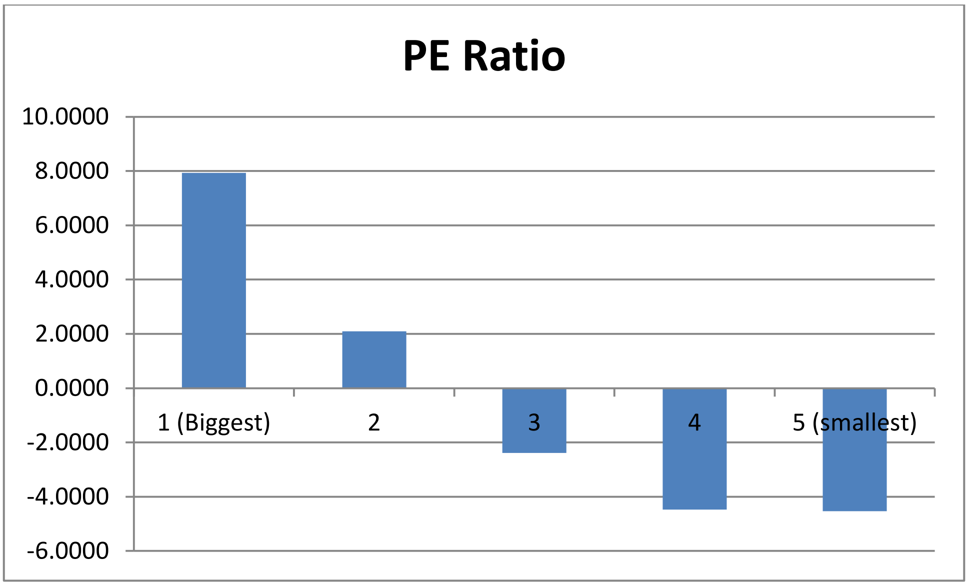


Figure 5.7 Average Price to Earnings ratios of five size sorted portfolios



In Table 5.3, the yearly variables are ranked by idiosyncratic volatility and sorted into five portfolios with an equal number of stocks in each portfolio. Portfolio 1 comprises the companies with highest idiosyncratic volatility and portfolio 5 comprises the companies with lowest idiosyncratic volatility. All portfolios are rebalanced on an annual basis. As size is negatively correlated with idiosyncratic volatility, the opposite patterns are expected in Table 5.3 to compared to those of Table 5.2. Table 5.3 shows results consistent with those reported in Table 5.2 and the patterns are shown in Figure 5.8 to Figure 5.13.

The statistics in Table 5.3 suggest patterns are evident in idiosyncratic volatility, Icover, ROE, PE and EPS. As expected, high idiosyncratic volatility companies are small by size, low in Icover, ROE, PE and EPS. In other words, the results presented in Table 5.3 further confirm that high idiosyncratic volatility companies are small by size, have low ability to meet debt obligation (measured by Icover), have low management performances (measured by ROE) and profitability (measured by EPS), and investors are willing to pay less for every dollar of earnings (measured by PE). There is not a clear pattern in dividend yield when moving from portfolio 1 to portfolio 5. Dividend yield increases when moving from portfolio 1 to portfolio 3, but it does not change much when moving from portfolio 3 to portfolio 5.

The results of Table 5.2 and 5.3 indicate that high idiosyncratic volatility companies have low earnings and high leverages. Low earnings lead to low EPS ratios implying that investors will not be willing to pay a high price for every dollar of earnings since a low EPS indicates poor company performance and a low ability to generate profits. Hence, it is reasonable to expect that these companies have the lowest PE. High leverage and low profitability also lead to an increase in volatility of earnings over time. Volatility in earnings is part of firm specific risk. Hence, high leverage and low profitability companies tend to have high idiosyncratic volatility. Overall, the results of portfolio analysis suggest that high idiosyncratic volatility companies are small, highly leveraged and low profitable. Investors are not willing to pay high prices for the earnings of the companies with high idiosyncratic volatility, so these companies have low PE.

Table 5.3 Equally weighted average of the variables in five idiosyncratic volatility sorted portfolios

Portfolios sorted by idiosyncratic volatility					
	1 (highest)	**2**	**3**	**4**	**5 (lowest)**
Size	0.8270	1.1242	1.5535	2.1149	2.3134
Dividend Yield	0.0344	0.0409	0.0443	0.0450	0.0442
Interest Cover Ratio	-26.8481	-21.9364	-11.2798	0.3008	3.8067
Return of Equity	-0.3649	-0.2196	-0.0862	0.0625	0.0878
EPS	0.0075	0.0172	0.0389	0.1093	0.1763
PE Ratio	-5.1012	-5.4231	-1.9451	4.6272	6.1745

Note. Size is scaled by taking natural logarithm, other variables are the levels. Idiovol is idiosyncratic volatility, Icover is interest cover ratio, PE is price-to-earnings ratio, ROE is ROE, and EPS is earnings per share. The portfolios are rebalanced on annual basis.

Figure 5.8 Average sizes of five idiosyncratic volatility sorted portfolios

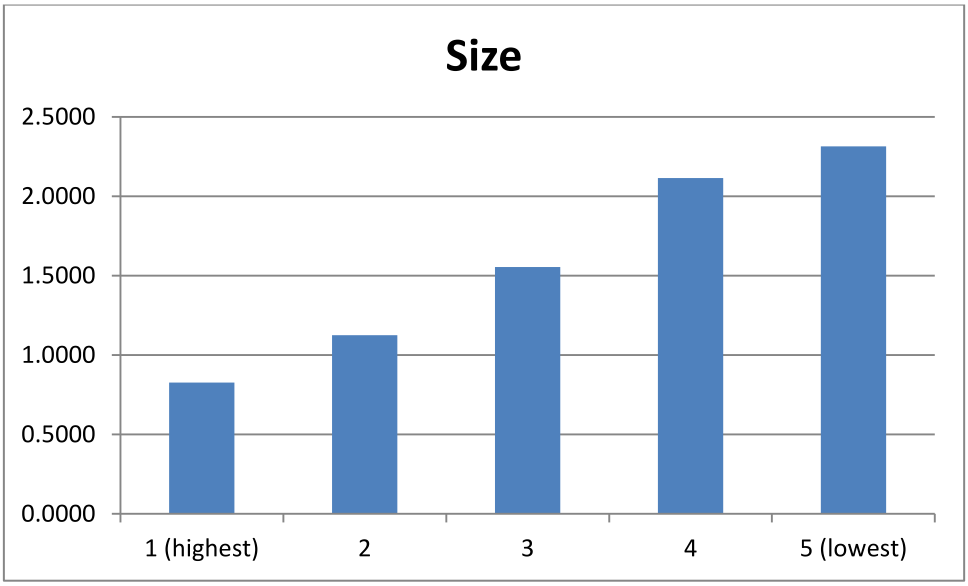


Figure 5.9 Average Dividend Yields of five idiosyncratic volatility sorted portfolios

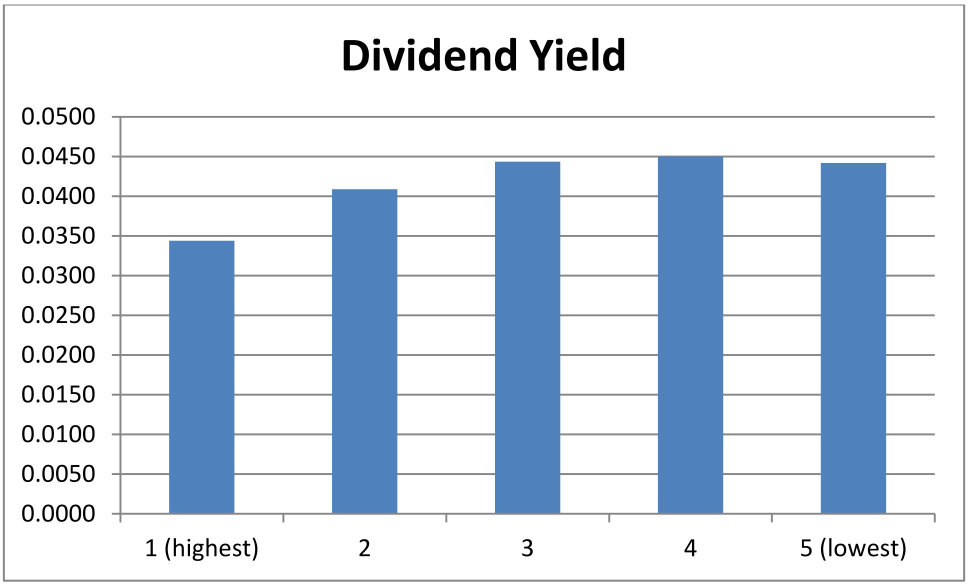


Figure 5.10 Average Interest Cover ratios of five idiosyncratic volatility sorted portfolios

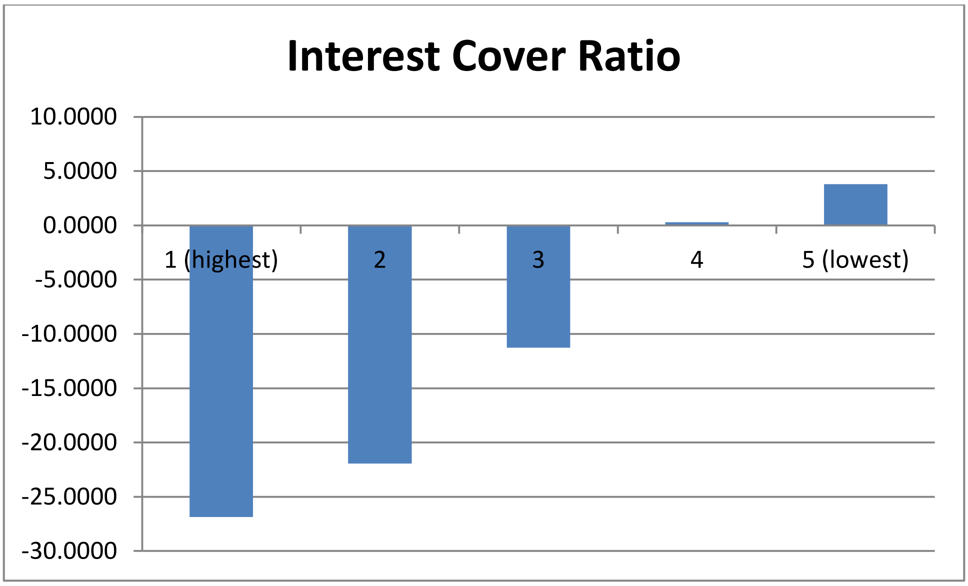


Figure 5.11 Average Return of Equity ratios of five idiosyncratic volatility sorted portfolios

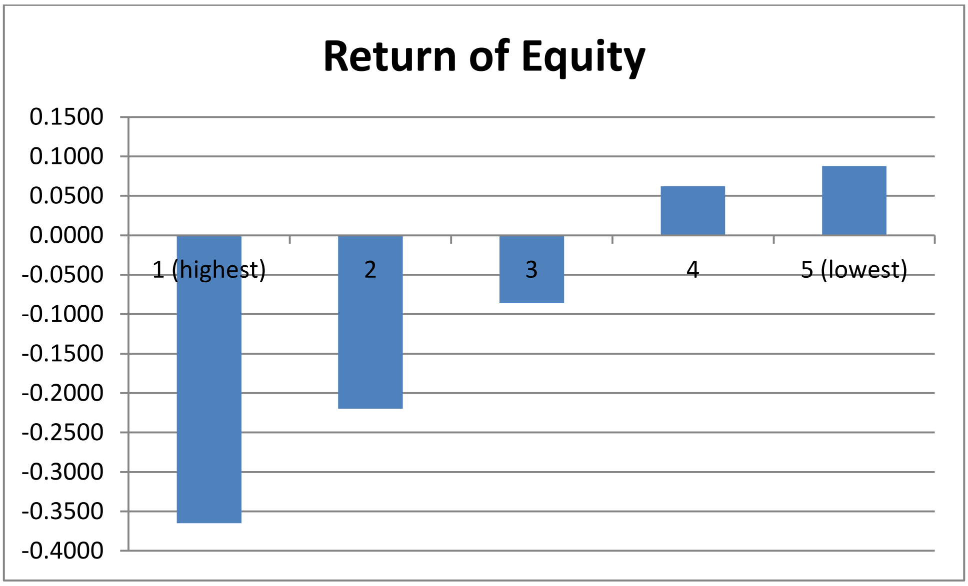


Figure 5.12 Average Earnings Per Share ratios of five idiosyncratic volatility sorted portfolios

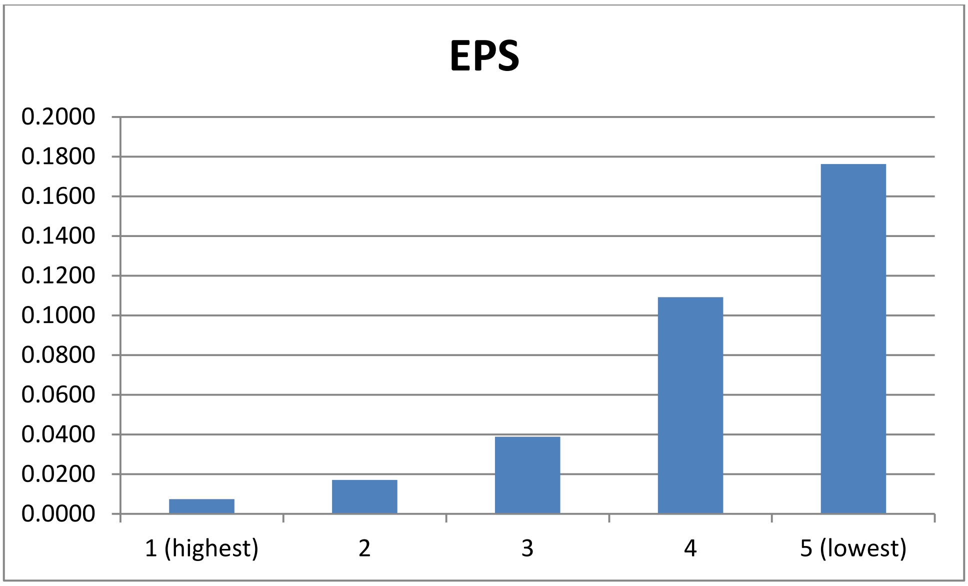
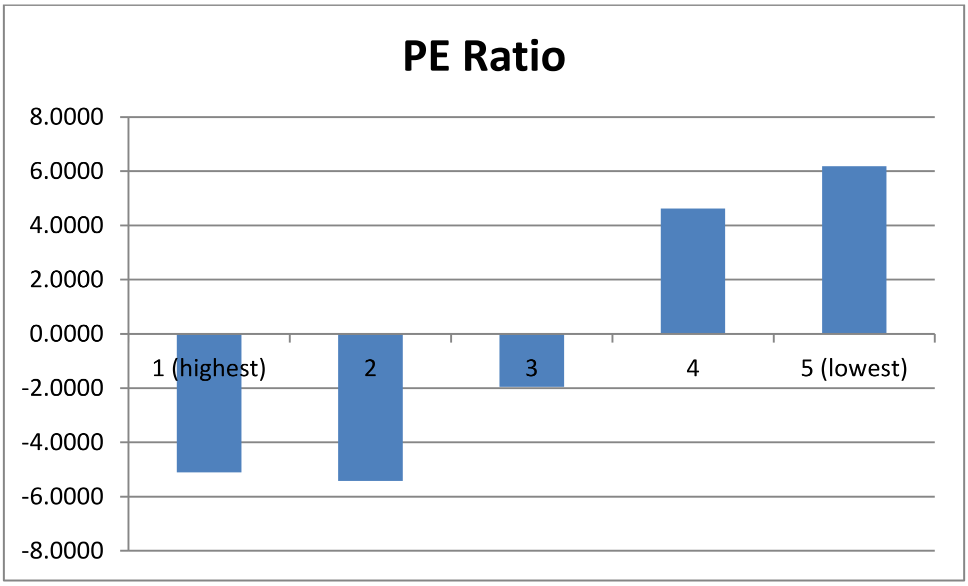


Figure 5.13 Average Price to Earnings ratios for five idiosyncratic volatility sorted portfolios



5.4.2. CROSS-SECTIONAL REGRESSION ANALYSIS

Table 5.4 compares the results of regressions denoted (a) to (g). The dependent variable is the idiosyncratic volatility. The independent variables are dividend yield, Icover, size (natural logarithm of size), PE, ROE and EPS.

In model (a), dividend yield and Icover are regressed with the idiosyncratic volatility. The coefficient on dividend yield is 0.0701 and it is statistically significant at the 1% level. The dividend yield coefficients are also statistically significant at the 1% level in other models and they are stable in all the models presented in the table. The evidence presented in Table 5.4 supports the hypothesis that the dividend yield is positively related to idiosyncratic volatility.

The Icover coefficient is statistically significant at 5%, but the negative relationship between Icover and the idiosyncratic volatility is not stable as the coefficients on Icover become insignificant in model (e), (f) and (g). In model (b), size is included in the regression equation. The size coefficient is statistically significant at the 1% level and negative. This suggests that when a company grows by size, it's idiosyncratic volatility decreases. This is consistent with the results of the portfolio analysis presented in Table 5.2 which shows that big companies tend to have low idiosyncratic volatilities whereas small companies tend to have high idiosyncratic volatilities.

In model (c), ROE is introduced into the regression function. The ROE coefficient is statistically significant at the 1% level and it has a negative sign, suggesting that higher level of the management performance (measured by ROE) the lower the idiosyncratic volatility for a company. The ROE coefficients are stable and statistically significant in model (d) and (g) supporting the hypothesis that ROE is negatively related to idiosyncratic volatility. This finding is consistent with Wei and Zhang (2004) as they find a negative relationship between ROE and the stock return volatility (largely idiosyncratic volatility) in the US from 1976 to 2000.

EPS is presented in the regression function for model (e). The coefficient on EPS is not statistically significant suggesting that EPS does not explain idiosyncratic volatility cross-sectionally. In model (f), PE is introduced into the regression function. The coefficient of PE is statistically significant at 5%. The coefficient has a negative sign suggesting that PE is negatively related to idiosyncratic volatility. As PE measures how much investors are willing to pay for every dollar of the company's earning, it is not surprising that investors are willing to pay more for companies with low idiosyncratic volatility companies but pay less for companies with high idiosyncratic volatility.

In model (g), all independent variables are included in the regression function. The coefficients on dividend yield, size, PE and ROE are statistically significantly. These coefficients are stable by magnitude and the t-statistics in all models reported in Table 5.4. Overall, the results show that dividend yield is positively related to idiosyncratic volatility, while PE, ROE are negatively related to the idiosyncratic volatility over the sample period. These relationships remain statistically significant in presence of size.

These negative relationships are consistent with economic rationale. For example, ROE measures how well a company uses its equity to generate profits. Companies with higher ROE ratios should have lower idiosyncratic volatility because the better a company uses its equity capital the lower the expected firm specific risk. PE can be used to measure a company's value and indicate how much investors should pay for every one dollar of company earnings. PE is closely related to a company's capital structure. Generally, highly leveraged companies tend to have lower PE ratios because leverage affects earnings and share prices. In other words, companies with higher levels of leverage tend to have lower PE ratios. Hence, the companies with lower PE ratios have higher risk profiles and more volatile earnings. Idiosyncratic risk measures firm specific risk which is a significant proportion of a company's total risk, so when the PE ratio of a company decreases, idiosyncratic volatility of the company increases and vice versa. This negative relationship between the PE ratio and idiosyncratic volatility is supported by economic rationale.

Table 5.4 Cross-sectional regression results

				Model			
	a	**b**	**c**	**d**	**e**	**f**	**g**
Intercept	0.01894***	0.0289***	0.0204***	0.0290***	0.0282***	0.0282***	0.0286***
t-stat	57.35	27.54	59.17	26.96	27.01	27.00	26.48
Dividend Yield	0.0701***	0.0723***	0.0657***	0.0659***	0.0736***	0.0736***	0.0660***
t-stat	10.90	11.22	10.21	10.21	11.50	11.49	10.17
Interest Cover Ratio	-0.00001**	-0.0000108**	-0.0000108**	-0.0000111**	-7.82E-06	-8.03E-06	-8.48E-06
t-stat	-2.19	-2.17	-2.12	-2.21	-1.57	-1.61	-1.66
Size		-0.0040***		-0.0035***	-0.0039***	-0.0039***	-0.0034***
t-stat		-10.01		-8.39	-9.72	-9.68	-8.28
PE Ratio						-0.00000404**	-0.00000329*
t-stat						-2.16	-1.83
ROE			-0.0153***	-0.0144***			-0.0135***
t-stat			-15.65	-14.74			-13.01
EPS					-1.81E-06	-1.79E-06	4.18E-07
t-stat					-0.19	-0.18	0.04
R^2	56%	57%	59%	60%	57%	57%	59%

Note. The dependent variable is the idiosyncratic volatility (idiovol). The independent variables are dividend yield, interest cover ratio, size (scaled by taking naturel logarithm), price to earnings ratio (PE ratio), return to equity (ROE), and earnings per share (EPS).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

5.4.3. DIVIDEND YIELD AND THE IDIOSYNCRATIC VOLATILITY

The empirical results show an interesting positive relationship between dividend yield and idiosyncratic volatility. The positive relationship is described as "interesting" because a negative relationship between dividend yield and the idiosyncratic volatility is consistent with economic theory.

According to the dividend signalling theory, the dividend yield signals a company's future prospects. Miller and Modigliani (1961) suggest that company's dividend policy has a signalling effect because investors interpret changes in dividend policy as reflecting management's expectations in regard to the company's future prospects. The dividend signalling theory suggests that an increase in dividend yield may indicate management's optimism about the future earnings of the company. Bhattacharya (1979), John and Williams (1985) and Miller and Rock (1985) further confirm the signalling property of dividend yield by developing dividend signalling models. These studies find evidence supporting the notion that investors interpret an increase in dividend yields as good news and a decrease in dividend yields as bad news. Hence a negative relationship between idiosyncratic volatility and dividend yield should be expected since companies with better future prospects should have lower firm specific risk or idiosyncratic volatility. However, contrary to this theory, this study finds a positive relationship between idiosyncratic volatility and dividend yield. One possible explanation for this finding is that increases in dividend payments over the sample period may have been made from liabilities and this consequently led to an increase in leverage of the listed companies. An increase in leverage is likely to lead to an increase in idiosyncratic volatility. Hence, the idiosyncratic volatility of the listed companies increased as dividend yields increased. This explanation is documented in Archarya, Gujral, Kulkarni and Shin (2011). They find that financial institutions worldwide raised new capital in debt and hybrid instruments from August 2007 to December 2012. During that time, financial institutions continued to pay dividends out of liabilities rather than earnings which further led to increases in leverage. As leverage increased, volatility of earnings also increased and consequently led to increases in idiosyncratic volatilities of these financial institutions. If this is the case for all the companies listed on ASX, then it is not surprising to observe a positive relationship between the idiosyncratic volatility and dividend yield over the sample period.

5.5. CONCLUSION

Using Australian stock market data, this chapter examines the relationship between idiosyncratic volatility and stock fundamental ratios. The empirical results suggest that big (small) companies tend to have low (high) idiosyncratic volatility, high (low) Icover, high (low) ROE, high (low) EPS and high (low) PE. In addition, the empirical results show a significant positive cross-sectional relationship between dividend yield and idiosyncratic volatility, a significant negative cross-sectional relationship between ROE and idiosyncratic volatility and a significant negative cross-sectional relationship between PE and idiosyncratic volatility. The results are robust when controlling for size.

In summary, for ASX listed companies from 1993 to 2010, high idiosyncratic volatility companies are small by size, have low ability to meet debt obligation (measured by Icover), have low management performance (measured by ROE) and low profitability (measured by EPS), and investors are willing to pay less for every dollar of earnings (measured by PE).

One interesting finding is the positive relationship between dividend yield and idiosyncratic volatility. According to the signalling effect of dividend yields, a negative relationship between the dividend yield and idiosyncratic volatility makes economic sense as an increase in dividend yield may indicate good news about a company's future prospects to the market and good news should lead to a decrease in idiosyncratic volatility. However, Archarya et al. (2011) document an undesirable nature of dividend payments. Specifically they find that financial institutions paid high dividends to shareholders out of newly raised liabilities from 2007 to 2012. If companies pay dividends from liabilities, this leads to an increase in leverage, and consequently an increase in return volatilities. If this was the case for ASX listed companies from 1993 to 2010, it is not surprising to see a positive relationship between dividend yield and idiosyncratic volatility. This study provides partial evidence to support that the leverage of ASX listed companies increased over the sample period as the average Icover increased. Further study is required to investigate the source of capital raised and sources of the funds used to make dividend payments by these ASX listed companies. This study indicates that there may be an interesting linkage between idiosyncratic volatility and corporate finance.

CHAPTER 6

6. ASSET PRICING FACTORS AND FUTURE ECONOMY GROWTH

6.1. INTRODUCTION

Asset pricing theories suggest that stock market information, for example stock prices and returns, reflect investors' expectations on the future earning of companies. As earnings of companies is part of GDP and highly correlated with other major economic indicators, such as company gross profit, CPI, import and export etc, the implication is that the stock market information may contain information about future economic growth. Thus, it is expected that stock prices may predict future economic growth.

A number of studies show that stock market information predicts economic activity. For example, Fama (1981) find that stock returns lead growth rates of GNP, capital expenditures, the return on capital and output. Fama (1981) suggests that current prices for securities are formed based on rational expectations on forecasts of real variables, so stock prices/returns may predict future economic activities. The leading role of stock market information has attracted a great level of attention, including Moore (1983), Fischer and Merton (1985), Barro (1990), Estrella and Mishkin (1998), Aylward and Glen (2000), Hassapis and Kalyvitis (2002), Panopoulou (2007), Ibrahim (2010). The finding presented in these studies support the views that stock market information leads economic activities.

Liew and Vassalou (2000) find that stock market return based asset pricing factors, such as Fama and French size factor (hereafter SMB) and book-to-market factor (hereafter HML), predict future economic growth across 10 developed countries including Australia. Liew and Vassalou (2000) suggest that SMB and HML are state variables in the context of Merton's (1973) intertemporal capital asset pricing model.

Liew and Vassalou (2000) successfully linked the return based asset pricing factors to the future growth rate of GDP and they find SMB predicts future economic growth for Australia from 1985 to 1996. Their results suggest asset pricing factors as sources of stock market information predict economic activity. Recent studies in the area of asset pricing find that idiosyncratic volatility is a significant asset pricing factor for stock returns even in the presence of Fama and French three-factor. For example, Ang et al. (2006, 2009) and Fu (2009) show that idiosyncratic volatility is priced in the US and internationally which suggests that idiosyncratic volatility contains important stock market information.

Idiosyncratic volatility is commonly measured as the standard deviation of the residual from the Fama and French three-factor regression model. It contains different information which is not captured by the Fama and French three-factor model. According to the literature, idiosyncratic volatility is expected to predict economic activity as it is an important source of stock market information. However, idiosyncratic volatility is a proxy of unsystematic risk. In other words, idiosyncratic volatility is not a state variable implying that it is not related to economic activities. Based on this point of view, idiosyncratic volatility should not predict economic activities. However the relationship between idiosyncratic volatility and economic activity has not been investigated in the literature. Therefore, this chapter is motivated to investigate whether idiosyncratic volatility, as an important source of stock market information, predicts the future growth rate of the Australian economy by using the regression models of Liew and Vassalou (2000).

The results of this study fill gaps in the literature. First, this study investigates the predictive power of Australian stock returns based on the Fama and French three-factor (MKT, SMB and HML) and an idiosyncratic volatility mimicking factor (hereafter HIMLI) to the growth rates of the Australian economy. Second, the set of economic variables has been expanded to ten major economic indicators compared to previous studies in the area, including the company gross profit index, the consumer price index (hereafter CPI), the export price index, the effective foreign exchange rate, the gross domestic products (hereafter GDP), the import price index, the industrial production index, M1, the Treasury bond rate and the unemployment rate index. The results revel the relationships between past returns of the asset pricing factors and different aspects of the future economy.

The empirical results show that (1) in general, the model consisting of all four asset pricing factors predicts growth rates of Australian macroeconomic indicators except M1 and the Treasury bond rate, (2) MKT has the strongest predictive power among four asset pricing factors, (3) SMB predicts GDP growth rate when HIMLI and AR(1) term are not presented in the regression model, (3) the predictive power of HIMLI is very weak, which suggest that HIMLI, the asset pricing factor mimicking idiosyncratic volatility, is not a state variable in the context of Merton's (1973).

The portfolio performance analysis results show that high past returns of SMB and HML portfolios precede periods of good states of the economy, but low past returns of HIMLI precede period of good states of the economic indicators. The finding of high past returns of SMB and HML precede good states of the economy is consistent with Liew and Vassalou (2000), but the negative relationship between past returns of HIMLI and future growth rates of the economic indicators is an interesting finding. In general, it is not surprising that high returns of the stock market factors precede periods of high growth rate of the economic indicators because current stock prices reflect investors' expectations on future earnings of the companies and the earnings of the companies are highly correlated with the economic indicators. Therefore, the negative relationship between HIMLI and the economic indicators is interesting and it is first reported in the literature to the author's knowledge.

The reminder of this chapter is organized as follows. Section 6.2 outlines the method employed in this study. Section 6.3 describes the data. Section 6.4 presents the empirical results and results discussion. Section 6.5 provides the conclusion.

6.2. METHODOLOGY

6.2.1. CONSTRUCTION OF FAMA AND FRENCH RISK MIMICKING PORTFOLIOS BY USING DAILY RETURNS AND ESTIMATION OF MONTHLY IDIOSYNCRATIC VOLATILITY

In this chapter, risk mimicking Fama and French three-factor and the idiosyncratic volatility factor are examined in regard to their predictability of the growth rate of ten key economic indicators in Australia. The first step is to estimate the monthly idiosyncratic volatility for stocks by constructing daily Fama and French risk mimicking portfolios.

Following Ang et al. (2009), idiosyncratic volatility is defined as the standard deviation of regression residuals of the Fama and French (1993) three-factor. In order to construct SMB and HML portfolios with daily stock returns, the stocks are sorted into two size portfolios and three BE/ME portfolios. The two size portfolios comprise the top 50% of companies (big) by market capitalization and the bottom 50% companies (small) by market capitalization. The three BE/ME portfolios comprise top 1/3 companies (high) by BE/ME, medium 1/3 companies by BE/ME and bottom 1/3 companies (low) by BE/ME.

These portfolios are rebalanced on an annual basis. At end of year, the companies are ranked and sorted into the six portfolios according to their size and BE/ME at December of year t-1. SMB is calculated as the return of the small size portfolios minus the return of the big size portfolio. HML is calculated as the returns of the high BE/ME portfolio minus the returns of the low BE/ME portfolio.

6.2.2. CONSTRUCTION OF RISK MIMICKING PORTFOLIOS FOR SIZE, BOOK-TO-MARKET AND IDIOSYNCRATIC VOLATILITY BY USING MONTHLY RETURNS

Again, SMB and HML portfolios with monthly stock returns are constructed by following Fama and French (1993). SMB is estimated as the monthly returns of the small size portfolio minus the monthly return of big size portfolio. HML is estimated as the monthly returns of the high BE/ME portfolio minus the monthly returns of the low BE/ME portfolio.

Then, following Fama and French (1993) and Drew, Naughton and Veeraraghavan (2004), the monthly risk mimicking portfolio for idiosyncratic volatility (HIMLI) is constructed. The stocks are sorted into three portfolios according to their idiosyncratic volatilities. Three idiosyncratic volatility portfolios comprise 1/3 high idiosyncratic volatility companies, 1/3 medium idiosyncratic volatility companies and 1/3 low idiosyncratic volatility. The monthly idiosyncratic volatility factor HIMLI is estimated as the returns of high idiosyncratic volatility portfolio minus the returns of low idiosyncratic volatility portfolio. The idiosyncratic volatility portfolios are rebalanced on an annual basis. Every year t, the companies are ranked and sorted into three portfolios according to their idiosyncratic volatilities at the December of the previous year.

After the construction of the monthly SMB, HML and HIMLI, the monthly asset pricing factors are converted to quarterly data by taking the average on three months of data in each quarter.

6.2.3. REGRESSION ANALYSIS

6.2.3.1. UNIVARIATE REGRESSIONS

Following Liew and Vassalou (2000), univariate regression analysis is employed to analyse the predictive power of the individual asset pricing factor to future economic growth. The regressions use quarterly data and the regression equation is the following:

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(Factor\,\mathrm{Re}turn_{(t-4,t)}) + \varepsilon_{(t,t+4)} \qquad (6.1)$$

Where $EconomyIndicator_{(t,t+4)}$ is the sum of quarterly growth rate of ten economic indicators from the period t to t+4 for Australia, including company gross profit index, consumer price index (hereafter CPI), export price index, effective foreign exchange rate, GDP, import price index, inflation, industrial production index, job advertisement index, M1, treasury bond rate and unemployment rate index; $Factor\,\mathrm{Re}turn_{(t-4,t)}$ is either sum of MKT, SMB, HML or HIMLI from the period t-4 to t; and ε is the regression residual.

The macroeconomic indicators generally have quarterly frequency, so serial correlation and heteroskedasticity in the regression residuals is suspected. Following Liew and Vassalou (2000), the Newey and West (1987) estimator is employed for the regressions to control these potential data problems.

6.2.3.2. BIVARIATE REGRESSIONS

Bivariate regression analysis is employed to test whether SMB, HML and HIMLI contain the same information as that of MKT. The regression equation is the following:

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(Factor\,\mathrm{Re}turn_{(t-4,t)}) + \varepsilon_{(t,t+4)} \qquad (6.2)$$

Where $EconomyIndicator$ is the growth rate of each of the ten Australian economic indicators; MKT is the quarterly market premium or excess return of the market portfolio over the risk free rate; $Factor\ Return$ is SMB, HML or HIMLI; and ε is the regression residual.

6.2.3.3. MULTIVARIATE REGRESSIONS

Furthermore, multivariate regression analysis is employed to examine the information contents of MKT, SMB, HML and HIMLI in regard to future economic growth in Australia. The regression results will reveal insights of that which model can predict which economic indicator for Australia. The regression equations are the following:

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(SMB_{(t-4,t)}) + \delta(HML_{(t-4,t)}) + \varepsilon_{(t,t+4)} \quad (6.3)$$

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(SMB_{(t-4,t)}) + \delta(HIMLI_{(t-4,t)}) + \varepsilon_{(t,t+4)} \quad (6.4)$$

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(HML_{(t-4,t)}) + \delta(HIMLI_{(t-4,t)}) + \varepsilon_{(t,t+4)} \quad (6.5)$$

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(SMB_{(t-4,t)}) + \delta(HML_{(t-4,t)}) + \lambda(HIMLI_{(t-4,t)}) + \varepsilon_{(t,t+4)} \quad (6.6)$$

6.2.3.4. PORTFOLIO PERFORMANCES ANALYSIS

The past one year returns of SMB, HML and HIMLI portfolios are sorted by 'good state' and 'bad state' of the following one year growth rate of the ten economic indicators. The results reveal what factors have high (low) returns preceding the good (bad) states of the economic indicators. Following Liew and Vassalou (2000), 'good state' of the economic indicator is defined as those states that exhibit the highest 25% of future growth, and 'bad state' of the economic indicator is defined as those states that exhibit the lowest 25% of future growth. The results reveal the relationship between the past four quarters' returns of SMB, HML and HIMLI portfolios and the next four quarters' growth rate of the ten Australian economic indicators.

6.3. DATA

The sample period for this study is from January 1993 to December 2010. Australian stock returns, market to book equity values, stock capitalisation data and the indices of ten major economic indicators are obtained from Datastream. The 90-day Australian Bank Accepted Bill Rate is obtained from the website of the Reserve Bank of Australia to represent a proxy for the risk free rate in Australia. ASX all ordinaries Total Return Index is used to represent the market portfolio proxy for Australia. The ten Australian major economic indicators, include the company gross profit index, the consumer price index (hereafter CPI), the export price index, the effective foreign exchange rate, the GDP, the import price index, the industrial production index, M1, the treasury bond rate and the unemployment rate index, are obtained from Datastream.

The initial sample includes both active and dead stocks listed on ASX during the sample period. To calculate monthly idiosyncratic volatility, the Fama and French BE/ME factor and the size factor are constructed by using daily stock returns. Subsequently the regression residuals are extracted to calculate the monthly idiosyncratic volatility. In order to avoid thin trading effects, stocks are required to have at least one trade in a month. The stocks are excluded from the initial sample if the stocks do not have the following available data during the sample period: daily and monthly total return, monthly market capitalization and monthly market to book value.

Table 6.1 summarizes the number of stocks in the final sample and their average returns, average size, average BE/ME and average idiosyncratic volatility over the sample period. The fewest number of stocks (422) is in 1993 and the largest number of stocks (1773 stocks) is in 2008 for the period 1993 to 2010.

Table 6.1 Summary statistics

Year	**Number of Stocks**	**Return**	**Size**	**BEME**	**Idiovol**
1993	422	0.0628	474	0.8564	0.1620
1994	480	0.0152	524	0.6741	0.1540
1995	529	0.0261	490	0.7701	0.1463
1996	737	0.0351	415	0.7110	0.1606
1997	822	-0.0087	435	0.7763	0.1712
1998	862	0.0029	514	0.9112	0.1954
1999	888	0.0480	637	0.8776	0.1983
2000	980	0.0182	655	0.7970	0.2106
2001	1083	-0.0003	619	1.0780	0.2162
2002	1111	0.0035	603	1.0110	0.2032
2003	1141	0.0433	573	0.9398	0.1972
2004	1255	0.0227	634	0.7465	0.1638
2005	1380	0.0065	716	0.7481	0.1705
2006	1485	0.0313	797	0.7193	0.1839
2007	1612	0.0237	912	0.6014	0.1860
2008	1773	-0.0649	723	0.8178	0.2591
2009	1771	0.0736	617	1.2262	0.2556
2010	1746	0.0179	765	0.8234	0.1989

Note. This table shows the average number of stocks, average monthly return, average size (in millions) of the companies, average monthly BE/ME, and average monthly idiosyncratic volatility over the sample period.

All ten economic indicators are quarterly data. The ten economic indicators show a common characteristic of macroeconomic data. As they are non-stationary data, all ten economic indicators are adjusted by taking the difference of the log of each series in order to make them stationary. After the adjustments are made, they are transformed to the growth rates of the ten economic indicators. Table 6.2 shows the descriptive statistics for the growth rates of the ten economic indicators used in the analysis.

Table 6.2 Descriptive summary statistics of ten Australia macroeconomic indicators

	Company profit	CPI	EXPORT	Effective exchange rate	GDP	IMPORT	IP	M1	T-BOND	Unemployment
Mean	0.0201	0.0062	0.0088	0.0048	0.0085	0.0002	0.0055	0.0207	-0.0048	-0.0104
Median	0.0220	0.0063	0.0034	0.0046	0.0080	-0.0009	0.0063	0.0230	-0.0195	-0.0126
Maximum	0.1548	0.0167	0.1491	0.1147	0.028	0.1021	0.0408	0.0521	0.2500	0.1636
Minimum	-0.1119	-0.0042	-0.2312	-0.2093	-0.0090	-0.0659	-0.0246	-0.1474	-0.2918	-0.0755
Std. Dev.	0.0446	0.0043	0.0557	0.0443	0.0059	0.0299	0.0124	0.0253	0.0888	0.0360
Skewness	-0.0826	0.0194	-0.5502	-1.3701	0.2771	0.5660	0.0434	-4.1548	0.1355	1.7919
Kurtosis	4.3013	3.1009	7.4177	9.3881	4.1798	3.7833	3.0786	28.4543	4.0278	9.5187
Jarque-Bera	4.6600	0.0345	61.3183	142.9380	5.0970	5.6062	0.0406	2121.0350	3.3422	163.7030
Probability	0.0973	0.9829	0.0000	0.0000	0.0001	0.0606	0.9799	0.0000	0.1880	0.0000
Sum	1.3039	0.4381	0.6248	0.3429	1.1118	0.0123	0.3877	1.4721	-0.3429	-0.7401
Sum Sq. Dev.	0.1274	0.0013	0.2168	0.1375	0.0056	0.0627	0.0107	0.0450	0.5515	0.0906
Observations	65	71	71	71	71	71	71	71	71	71

The results in Table 6.2 report the economic indicators have positive average quarterly growth rates except the T-bond rate and the unemployment rate, suggesting that on average, the Australian economy performed positively from 1993 to 2010. The negative average growth rate of the T-bond rate and the unemployment rate suggest both rates dropped on average over the period. The growth rate of CPI is 0.62% per quarter on average and the GDP growth rate is 0.85% per quarter over the sample period. The growth rate of the effective exchange rate is 0.48% per quarter which suggests that value of Australian dollar appreciated by 0.48% against the currencies of its major trading partners on average. The growth rate of export index is 0.88% per quarter which is much higher than the growth rate of the import index of 0.02% per quarter.

The returns of the asset pricing factors are monthly data. The monthly asset pricing factors are converted to quarterly frequency by taking the average of three monthly observations in a quarter. Table 6.3 shows the descriptive statistics of the quarterly asset pricing factors, which are the market factor, the size factor, the BE/ME factor and the idiosyncratic volatility factor. These asset pricing factors are used as the independent variables in the regressions.

Table 6.3 Descriptive summary statistics of the asset pricing factors

	MKT	SMB	HML	HIMLI
Mean	0.004873	0.009392	0.018831	0.016075
Median	0.006639	0.007473	0.016954	0.023782
Maximum	0.068494	0.059759	0.074452	0.208122
Minimum	-0.114416	-0.022343	-0.023987	-0.088342
Std. Dev.	0.025644	0.018254	0.019238	0.049354
Skewness	-1.446069	0.510173	0.400691	0.751997
Kurtosis	8.689823	3.118737	3.349261	5.050017
Jarque-Bera	122.2156	3.165617	2.292588	19.3937
Probability	0	0.205397	0.317812	0.000061
Sum	0.350822	0.676207	1.355825	1.157397
Sum Sq. Dev.	0.046691	0.023659	0.026278	0.172942
Observations	72	72	72	72

Note. MKT is the market factor, SMB is the size factor, HML is the book-to-market factor and HIMLI is the idiosyncratic volatility factor.

6.4. EMPIRICAL RESULTS

6.4.1. UNIVARIATE REGRESSION RESULTS

Table 6.4 shows the results of univariate regressions of future growth rate of Australian economic indicators on past returns of the MKT, SMB, HML or HIMLI. The coefficients of the univariate regressions are presented.

Table 6.4 Univariate regressions results

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(Factor\ \mathrm{Re}turn_{(t-4,t)}) + \varepsilon_{(t,t+4)}$$

Panel A																				
Economy indicators	Slope coefficients					T-stat					R^2					Durbin-Watson Stat			
	MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI
Company gross profit	0.81	0.38	0.01	0.02		3.73	1.20	0.03	0.14		29.2%	4.0%	0.0%	0.0%		0.68	0.58	0.53	0.53
Consumer price index	0.04	0.03	0.05	0.04		1.56	0.61	1.25	2.05		2.8%	0.8%	5.8%	9.8%		0.24	0.23	0.22	0.27
Export price index	1.47	1.44	-0.44	0.54		7.36	4.75	-1.28	4.26		40.4%	22.4%	3.7%	20.8%		0.53	0.52	0.43	0.52
Effective exchange rate	-0.65	-0.17	0.74	-0.13		-2.91	-0.51	3.32	-0.95		16.4%	0.7%	21.3%	2.7%		0.50	0.45	0.59	0.46
GDP	0.23	0.17	0.05	0.05		3.40	2.72	1.24	1.62		36.3%	11.9%	1.8%	5.6%		0.50	0.37	0.34	0.33
Import price index	0.68	0.46	-0.59	0.20		4.08	1.77	-2.69	1.80		25.3%	6.6%	18.8%	8.8%		0.44	0.39	0.47	0.42
Industrial Production	0.05	0.02	-0.12	0.07		0.67	0.29	-1.52	2.85		1.6%	0.1%	9.4%	11.5%		0.54	0.52	0.56	0.59
M1	0.32	0.27	-0.44	0.19		3.67	0.90	-2.67	2.00		10.5%	4.1%	19.4%	14.1%		0.46	0.40	0.55	0.43
Treasury bond rate	-0.13	-0.19	0.36	-0.11		-0.25	-0.39	0.95	-0.48		0.2%	0.2%	1.6%	0.5%		0.66	0.65	0.68	0.66
Unemployment rate	-0.86	-0.04	0.17	0.00		-2.87	-0.13	0.68	0.00		20.4%	0.0%	0.8%	0.0%		0.29	0.23	0.24	0.23

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(Factor\ \mathrm{Re}turn_{(t-4,t)}) + AR(1) + \varepsilon_{(t,t+4)}$$

Panel B																				
Economy indicators	Slope coefficients					T-stat					R^2					Durbin-Watson Stat			
	MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI		MKT	SMB	HML	HIMLI
Company gross profit	0.67	0.00	0.07	0.12		3.07	0.01	0.18	0.98		58%	51%	51%	52%		1.43	1.25	1.25	1.23
Consumer price index	0.00	0.00	0.05	0.01		0.19	-0.19	1.91	1.12		78%	78%	80%	78%		1.19	1.18	1.09	1.17
Export price index	1.35	0.89	-0.11	0.31		5.54	2.15	-0.24	2.34		72%	65%	62%	64%		1.30	1.03	0.87	1.08
Effective exchange rate	-0.56	-0.14	0.43	-0.06		-2.29	-0.49	2.05	-0.86		62%	59%	60%	59%		1.37	1.29	1.34	1.29
GDP	0.15	0.12	0.06	0.05		2.11	1.50	0.78	1.87		72%	70%	68%	70%		1.41	1.23	1.14	1.13
Import price index	0.54	0.25	-0.25	0.05		3.46	1.16	-1.28	0.83		71%	66%	66%	66%		1.40	1.32	1.26	1.31
Industrial Production	-0.02	0.01	-0.10	0.04		-0.23	0.12	-0.98	1.19		53%	53%	55%	54%		1.33	1.33	1.33	1.32
M1	0.10	0.17	-0.05	0.13		1.00	0.88	-0.32	1.29		64%	64%	64%	66%		1.35	1.40	1.33	1.39
Treasury bond rate	-0.45	-0.69	0.23	-0.16		-0.86	-1.29	0.39	-0.83		41%	42%	41%	41%		1.61	1.59	1.58	1.60
Unemployment rate	-0.41	-0.36	-0.14	-0.06		-1.96	-1.03	-0.47	-0.48		79%	78%	77%	78%		0.99	1.00	0.96	0.95

Note. The dependent variables are ten major Australian economic indicators. The independent variables are portfolios returns including MKT, SMB, HML and HIMLI. MKT is the excess return on the accumulative ASX All Ordinary Index, SMB is Fama and French risk factor mimicking portfolio for size, HML is Fama and French risk factor mimicking portfolio for book-to-market equity ratio and HIMLI is a risk factor mimicking portfolio for idiosyncratic volatility. Serial correlation and heteroskedasticity in the residuals of the regressions is controlled by using Newey and West (1987) estimator.

In Panel A, seven out of ten coefficients are statistically significant in the case of MKT as the independent variable. The regressions for consumer price index, industrial production and the Treasury bond rate produce insignificant coefficients which suggest that past returns of MKT do not predict growth rates of these economic indicators. Five out of seven significant coefficients show positive signs which suggest positive relationships between past returns of MKT and future growth rate of the company gross profit, the export price index, GDP, the import price index, and M1.

This may indicate that investors buy equities when they expect these economic indicators will grow at a faster rate in the future because generally faster growth rates for these economic indicators can be interpreted as good news[16] in the economy. Two out of seven significant coefficients have negative signs which suggest negative relationships between past returns of MKT and the future growth rate of the effective foreign exchange rate and the unemployment rate. This may indicate that investors sell stocks when they expect growth rates of these economic indicators will increase in the future as increases in the growth rate of effective foreign exchange rate and unemployment rate can be interpreted as bad news in the economy.

Three out of ten coefficients are statistically significant in the case of SMB as an independent variable. The three coefficients are positive which suggests positive relationships between past returns of SMB and future growth rate of export price index, GDP, and the import price index. These results are consistent with Liew and Vassalou

[16] Increase in M1 can be interpreted as either good or bad news in the economy which depends on various factors and economic conditions. A moderate increase in growth rate of M1 can be good news to Australian economy over the sample period.

(2000) who suggest high returns of SMB precede periods of high economic growth. Three out of ten coefficients are statistically significant in the case of HML as an independent variable. In the case of effective foreign exchange rate, the slope coefficient is positive. For the import price index and M1, the slope coefficients are negative.

Five out of ten slope coefficients are statistically significant in the case of HIMLI as an independent variable. The five slope coefficients are positive which suggests that a positive relationship between past returns of HIMLI and the growth rates of the consumer price index, the export price index, the import price index, industrial production and M1.

However, the Durbin-Watson statistics of the univariate regressions indicate autocorrelation in the model. In order to correct this problem, an AR(1) term is added into the regression models. In Panel B, the coefficients of the independent variables are summarized. After an AR(1) term is included in the regressions, the number of significant coefficients for MKT decreases to six out of ten compared to seven out of ten in Panel A of Table 6.4. The magnitude of the significant coefficients of MKT are similar when the AR(1) term is included in the regressions. The signs of the significant coefficients remain the same which suggests the relationship between MKT and the economic indicators is robust.

There is one significant coefficient for SMB when consumer price index is a dependent variable. This indicates that high returns of SMB precede a high export price index because generally a high export price index can be interpreted as a good new[17] in the economy. There are two significant coefficients for HML in Panel B of Table 6.4. The coefficients of HIMLI are significant when the consumer price index and the effective

[17] As high demand for exports lead to increase in export price index.

exchange rate are dependent variables. Both significant coefficients of HML have positive signs which indicate that a high HML return also precedes high growth rates of the consumer price index and the effective foreign exchange rate. The number of significant coefficients for HIMLI decreases to two compared to five in Panel A of Table 6.4. The coefficients of HIMLI are significant in the cases when the export price index and GDP are the dependent variable. Both coefficients have positive signs which suggest that high returns of HIMLI precede high growth rates of the export price index and GDP.

In Panel B of Table 6.4, the results show that the values of adjusted R-squared improve significantly after an AR(1) term is added to the regressions. Importantly, the Durbin-Watson statistics suggest that autocorrelation is not a serious problem. Therefore, it can be concluded that the univariate regression analysis shows that MKT contains the most information among the four asset pricing factors but SMB, HML and HIMLI also contain information in relation to the future growth rate of the economic indicators.

6.4.2. BIVARIATE REGRESSION RESULTS

The results of univariate regression analysis suggest that MKT contains the most information in relation to the future growth rate of economy. In this section, the information contents of SMB, HML or HIMLI are examined in the presence of MKT by using bivariate regression analysis.

Table 6.5 shows the results of bivariate regressions analysis. In Panel A, Model 1 of Table 6.5 shows that in the presence of MKT, the slope coefficients of SMB remain significant and are positive. The past returns of MKT have strong predictive power for the future growth rate of seven out ten Australian economic indicators. This is consistent with the results of the univariate regression analysis in Panel A of Table 6.4. In the presence of MKT, three out of ten slope coefficients remain statistically significant which suggests that the information content of SMB is different to the information content of MKT.

The results of Model 2 in Table 6.5 report four out of ten slope coefficients of HML remain statistically significant in the presence of MKT and the number of significant slope coefficients of HML increases to four compared to three significant slope coefficients for the univariate regression analysis. This suggests that the predictive power of HML improves in the presence of MKT. However, there are no big changes in the magnitude of the HML coefficients and there is no change in the sign of the significant coefficients for HML in the presence of MKT.

The results of Model 3 reported in Table 6.5 show three out of ten slope coefficients of HIMLI remain statistically significant in the presence of MKT compared to five significant coefficients for the univariate regressions in Panel A of Table 6.4. The bivariate regression results suggest MKT, SMB, HML and HIMLI contain information in regard to future growth rates of the economic activities. However, the low Durbin-Watson statistics suggest that autocorrelation exists in the models. In Panel B of Table 6.5, the same bivariate regressions are run again in presence of an AR(1) term.

In Panel B of Table 6.5, the coefficients of MKT remain stable in the presence of an AR(1) term except the coefficient of MKT becomes insignificant in the case of M1 as a dependent variable. The results of the bivariate regression analysis suggest that the information content of SMB, HML an HIMLI is different to the information content of MKT.

Table 6.5 Bivariate regression results

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(Factor\ \mathrm{Re}turn_{(t-4,t)}) + \varepsilon_{(t,t+4)}$$

Panel A: Model 1							
Economy indicators	MKT			SMB			
	Slope	T-stat		Slope	T-stat	R^2	Durbin Watson
Company gross profit	0.785	3.38		0.182	0.53	27.6%	0.71
Consumer price index	0.035	1.51		0.017	0.40	0.0%	0.24
Export price index	1.307	6.34		1.107	3.61	51.7%	0.73
Effective exchange rate	-0.649	-2.82		-0.009	-0.03	13.6%	0.50
GDP	0.210	3.04		0.118	1.82	39.8%	0.56
Import price index	0.636	3.76		0.295	1.26	25.6%	0.47
Industrial Production	0.009	0.13		0.066	2.50	8.6%	0.54
M1	0.295	3.47		0.191	0.65	9.6%	0.47
Treasury bond rate	-0.107	-0.20		-0.158	-0.32	-2.9%	0.65
Unemployment rate	-0.889	-2.78		0.189	0.57	18.3%	0.30
Model 2							
Economy indicators	MKT			HML			
	Slope	T-stat		Slope	T-stat	R^2	Durbin Watson
Company gross profit	0.902	4.61		0.281	0.86	30.1%	0.71
Consumer price index	0.062	2.28		0.075	1.62	9.8%	0.26
Export price index	1.485	7.52		0.047	0.14	38.5%	0.53
Effective exchange rate	-0.455	-2.52		0.594	2.86	26.1%	0.60
GDP	0.273	4.76		0.142	2.69	47.1%	0.65
Import price index	0.545	4.19		-0.407	-2.01	31.1%	0.51
Industrial Production	0.011	0.17		-0.117	-1.58	6.5%	0.56
M1	0.200	2.41		-0.376	-2.12	20.4%	0.57
Treasury bond rate	-0.013	-0.02		0.358	0.63	-1.6%	0.68
Unemployment rate	-0.905	-2.90		-0.133	-0.44	18.2%	0.29
Model 3							
Economy indicators	MKT			HIMLI			Durbin Watson
	Slope	T-stat		Slope	T-stat	R^2	
Company gross profit	0.861	3.55		-0.096	-0.98	28.2%	0.69
Consumer price index	0.017	0.67		0.033	1.70	7.4%	0.28
Export price index	1.263	6.05		0.335	3.35	46.0%	0.67
Effective exchange rate	-0.629	-2.72		-2.721	-0.24	13.8%	0.51
GDP	0.221	3.18		0.010	0.43	34.5%	0.50
Import price index	0.614	3.75		0.105	0.99	25.0%	0.49
Industrial Production	0.009	0.13		0.066	2.50	8.6%	0.60
M1	0.228	2.38		0.154	1.52	16.1%	0.49
Treasury bond rate	-0.072	-0.13		-0.095	-0.41	-2.7%	0.66
Unemployment rate	-0.955	-3.09		0.152	1.41	20.1%	0.30

Table 6.5 Bivariate regression results (continued)

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(Factor\ \mathrm{Re}turn_{(t-4,t)}) + AR(1) + \varepsilon_{(t,t+4)}$$

Panel B:model 1							
Economy indicators	MKT			SMB			
	Slope	T-stat		Slope	T-stat	R^2	Durbin-Watson
Company gross profit	0.71	3.14		-0.19	-0.61	58%	1.43
Consumer price index	0.01	0.24		-0.01	-0.26	78%	1.19
Export price index	1.27	5.19		0.56	1.75	73%	1.37
Effective exchange rate	-0.58	-2.15		0.07	0.24	62%	1.37
GDP	0.14	2.11		0.08	1.18	73%	1.44
Import price index	0.53	2.96		0.07	0.29	70%	1.42
Industrial Production	-0.02	-0.25		0.01	0.21	53%	1.33
M1	0.06	0.58		0.14	0.68	64%	1.39
Treasury bond rate	-0.33	-0.57		-0.56	-1.01	41%	1.62
Unemployment rate	-0.36	-1.89		-0.21	-0.68	79%	1.01
Model 2							
Economy indicators	MKT			HML			
	Slope	T-stat		Slope	T-stat	R^2	Durbin-Watson
Company gross profit	0.72	3.21		0.24	0.67	58%	1.42
Consumer price index	0.01	0.52		0.06	1.90	79%	1.11
Export price index	1.38	5.23		0.16	0.39	72%	1.29
Effective exchange rate	-0.52	-2.20		0.34	1.90	63%	1.43
GDP	0.17	2.54		0.10	1.48	73%	1.45
Import price index	0.52	3.58		-0.17	-0.96	70%	1.43
Industrial Production	-0.03	-0.54		-0.11	-1.11	54%	1.33
M1	0.10	0.90		-0.03	-0.22	63%	1.35
Treasury bond rate	-0.42	-0.77		0.13	0.22	41%	1.61
Unemployment rate	-0.44	-2.24		-0.23	-0.80	79%	0.98
Model 3							
Economy indicators	MKT			HIMLI			
	Slope	T-stat		Slope	T-stat	R^2	Durbin-Watson
Company gross profit	0.68	3.06		-0.01	-0.16	57%	1.43
Consumer price index	0.00	-0.17		0.01	1.16	78%	1.16
Export price index	1.28	5.06		0.10	1.17	72%	1.36
Effective exchange rate	-0.60	-2.04		0.05	0.45	62%	1.36
GDP	0.13	1.79		0.02	1.43	72%	1.39
Import price index	0.59	3.26		-0.06	-0.92	70%	1.33
Industrial Production	-0.06	-0.75		0.05	1.38	54%	1.33
M1	-0.03	-0.20		0.14	1.13	66%	1.38
Treasury bond rate	-0.38	-0.62		-0.10	-0.41	41%	1.62
Unemployment rate	-0.45	-2.16		0.04	0.40	79%	1.00

Note. The dependent variables are 10 major Australian economic indicators. The independent variables are portfolios returns including MKT, SMB, HML and HIMLI. MKT is the excess return on the accumulative ASX All Ordinary Index, SMB is Fama and French risk factor mimicking portfolio for size, HML is Fama and French risk factor mimicking portfolio for book-to-market equity ratio and HIMLI is a risk factor mimicking portfolio for idiosyncratic volatility. Serial correlation and heteroskedasticity in the residuals of the regressions is controlled by using Newey and West (1987) estimator.

6.4.3. MULTIVARIATE REGRESSION RESULTS

Table 6.6 presents the relationship between future growth rate of Australian economic indicators and past returns of MKT, SMB, HML and HIMLI. The results of multivariate regressions without the AR(1) term are summarized in In Panel A of Table 6.6 and the results of multivariate regressions with AR(1) term are summarized in Panel B of Table 6.6.

In both Panel A and B, the sign and magnitude of the slope coefficients of MKT are relatively stable in the presence of SMB, HML and HIMLI. In Panel A, the coefficients of MKT remain statistically significant in seven out of ten cases. In Panel B, the coefficients of MKT remain statistically significant in six out of ten cases. This suggests that past returns of MKT have significant predictive power in relation to the future growth rate of the economic indicators.

In Panel A, four out of ten slope coefficients of SMB remain statistically significant. In addition, four out of ten slope coefficients of HML remain statistically significant. HIMLI has the least number of significant slope coefficients among the four predictive variables, and only three out ten slope coefficients remain significant in the presence the MKT, SMB and HML. In Panel B, all coefficients of SMB become insignificant after an AR(1) term is included in the model. The number of significant coefficients for HML decreases from four to two when compared to those in Panel A and they are significant at the 5% level.

Turning our attention to the coefficients of HIMLI in Panel B, there are three significant coefficients when CPI, the import price index and industrial production are the dependent variables. However, these coefficients are only significant at the 10% level which suggests that HIMLI has weak predictive power in relation to the future growth rates of these three economic indicators.

Overall, the results presented in Table 6.6 suggest that the idiosyncratic volatility factor HIMLI is very weak in predicting future economic growth in Australia. These findings support the notion that the idiosyncratic volatility factor is not a state variable. Hence, it does not predict the future growth rate of the Australian economy very well. However, MKT and HML have a stronger predictive power, with MKT having the strongest predictive power in relation to the growth rate of the Australian economy compared to other three asset pricing factors.

6.4.4. PORTFOLIO PERFORMANCE ANALYSIS RESULTS

Table 6.7 reports the performance of the SMB, HML and HIMLI portfolios during good states and bad states of Australian economic indicators.

High returns of the SMB portfolio precede periods of high growth rates of the economic indicators in eight out of ten cases. The positive relationship between past one year returns of the SMB portfolio and one year ahead growth rates of the economic indicators are observed for company gross profit, the consumer price index, the export price index, GDP, industrial production, the treasury bond rate, and the unemployment rate. On average, the SMB portfolio generates a 0.8% return during good states and a 0.59% return during bad states. Generally, past one year returns of SMB are positively related to one year ahead growth rates of the economy.

High returns of the HML portfolio precede periods of high growth rate of the economy in seven out of ten cases. The positive relationship between past one year returns of HML portfolio and one year ahead growth rates of the economic indicators are observed for company gross profit, the consumer price index, the effective foreign exchange rate, GDP, and the Treasury bond rate. On average, the HML portfolio generates a 1.87% return during good states and a 1.63% during bad states.

Table 6.6 Multivariate regressions results

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(SMB_{(t-4,t)}) + \delta(HML_{(t-4,t)}) + \lambda(HIMLI_{(t-4,t)}) + \varepsilon_{(t,t+4)}$$

Panel A

Economy indicators	MKT			SMB			HML			HIMLI		R^2	Durbin-Watson
	Slope	T-stat		Slope	T-stat		Slope	T-stat		Slope	T-stat		
Company gross profit	0.885	3.99		0.468	1.83		0.135	0.40		-0.204	-2.18	31.6%	0.82
Consumer price index	0.050	1.76		-0.131	-2.12		0.125	2.57		0.077	3.00	30.0%	0.46
Export price index	1.245	5.33		0.996	2.33		-0.077	-0.32		0.085	0.65	50.6%	0.75
Effective exchange rate	-0.442	-2.31		-0.374	-0.93		0.700	3.80		0.125	0.76	25.4%	0.63
GDP	0.256	4.14		0.080	1.12		0.130	2.36		0.003	0.11	48.3%	0.68
Import price index	0.475	3.69		0.544	1.90		-0.522	-3.10		-0.077	-0.60	34.8%	0.58
Industrial Production	-0.010	-0.14		-0.108	-1.24		-0.067	-0.97		0.086	2.73	13.2%	0.61
M1	0.129	1.27		0.166	0.51		-0.372	-1.67		0.078	0.72	24.0%	0.61
Treasury bond rate	0.036	0.06		-0.277	-0.34		0.406	0.57		0.011	0.03	-4.6%	0.67
Unemployment rate	-0.975	-2.95		-0.022	-0.05		-0.072	-0.21		0.150	0.79	17.5%	0.30

$$EconomyIndicator_{(t,t+4)} = \alpha + \beta(MKT_{(t-4,t)}) + \gamma(SMB_{(t-4,t)}) + \delta(HML_{(t-4,t)}) + \lambda(HIMLI_{(t-4,t)}) + AR(1) + \varepsilon_{(t,t+4)}$$

Panel B

Economy indicators	MKT			SMB			HML			HIMLI		R^2	Durbin-Watson
	Slope	T-stat		Slope	T-stat		Slope	T-stat		Slope	T-stat		
Company gross profit	0.71	2.83		-0.41	-1.19		0.27	0.76		0.11	1.08	57%	1.39
Consumer price index	0.00	0.08		-0.04	-1.35		0.06	2.15		0.02	1.97	79%	1.12
Export price index	1.30	4.86		0.59	1.36		0.09	0.26		-0.03	-0.30	72%	1.35
Effective exchange rate	-0.56	-1.95		-0.09	-0.25		0.35	2.08		0.08	0.56	62%	1.43
GDP	0.15	2.39		0.05	0.69		0.10	1.65		0.01	0.71	73%	1.45
Import price index	0.57	3.20		0.33	1.08		-0.19	-1.04		-0.14	-1.76	70%	1.35
Industrial Production	-0.07	-0.93		-0.10	-1.15		-0.09	-1.02		0.07	1.69	55%	1.31
M1	-0.03	-0.19		-0.17	-0.87		0.01	0.04		0.18	1.17	65%	1.35
Treasury bond rate	-0.33	-0.50		-0.84	-1.02		0.21	0.39		0.14	0.40	40%	1.62
Unemployment rate	-0.47	-2.62		-0.47	-1.45		-0.21	-0.73		0.15	1.47	79%	1.04

Note. The dependent variables are ten major Australian economic indicators. The independent variables are portfolios returns including MKT, SMB, HML and HIMLI. MKT is the excess return on the accumulative ASX All Ordinary Index, SMB is Fama and French risk factor mimicking portfolio for size, HML is Fama and French risk factor mimicking portfolio for book-to-market equity ratio and HIMLI is a risk factor mimicking portfolio for idiosyncratic volatility. Serial correlation and heteroskedasticity in the residuals of the regressions is controlled by using Newey and West (1987) estimator.

Table 6.7 Performance analysis results

Economic indicator											
	SMB				HML				HIMLI		
	Good states	Bad states	Difference		Good states	Bad states	Difference		Good states	Bad states	Difference
Company gross profit	0.78%	0.02%	0.76%		1.93%	1.27%	0.66%		0.83%	0.14%	0.69%
Consumer price index	0.91%	0.60%	0.31%		2.13%	1.03%	1.10%		1.82%	2.25%	-0.42%
Export price index	0.74%	0.01%	0.73%		1.87%	2.06%	-0.19%		0.72%	-0.88%	1.60%
Effective exchange rate	0.40%	0.82%	-0.42%		2.17%	1.63%	0.55%		-0.06%	0.15%	-0.20%
GDP	0.77%	0.56%	0.21%		1.71%	1.57%	0.14%		1.35%	1.82%	-0.46%
Import price index	0.82%	0.85%	-0.03%		1.73%	1.81%	-0.08%		0.49%	2.12%	-1.63%
Industrial Production	1.27%	-0.08%	1.36%		1.11%	1.87%	-0.76%		2.26%	0.52%	1.74%
M1	0.85%	1.11%	-0.26%		1.32%	2.44%	-1.12%		3.88%	1.47%	2.41%
Treasury bond rate	0.66%	0.66%	0.00%		3.02%	1.08%	1.94%		1.08%	1.63%	-0.55%
Unemployment rate	1.35%	0.56%	0.79%		0.86%	2.53%	-1.67%		2.56%	1.39%	1.16%
AVERAGE	0.80%	0.59%	0.21%		1.87%	1.63%	0.25%		1.13%	1.37%	-0.24%

Note. “good states” is defined as those states that exhibit the highest 25% of future growth, and “bad states” as those states that exhibit the lowest 25% of future growth. SMB, HML and HIMLI are annually rebalanced portfolios. SMB is Fama and French risk factor mimicking portfolio for size and calculated as the returns of small size portfolio minus big size portfolio. HML is Fama and French risk factor mimicking portfolio for book-to-market equity ratio and calculated as the returns of high book-to-market equity ratio portfolio minus the returns of low book-to-market equity ratio portfolio. HIMLI is a risk factor mimicking portfolio for idiosyncratic volatility and is calculated as the returns of high idiosyncratic volatility portfolio minus the returns of low idiosyncratic volatility portfolio.

However, a negative relationship between past one year returns of HIMLI portfolio and the one year ahead growth rate of the economic indicators are observed for six out of ten cases. On average, the HIMLI portfolio generates a 1.13% return precede good states and a 1.37% return precede bad time. The HIMLI portfolio generates higher (lower) returns precede bad (good) states of the macro economy. Generally, past one year returns of HIMLI are negatively related to the one year ahead growth rate of the economy.

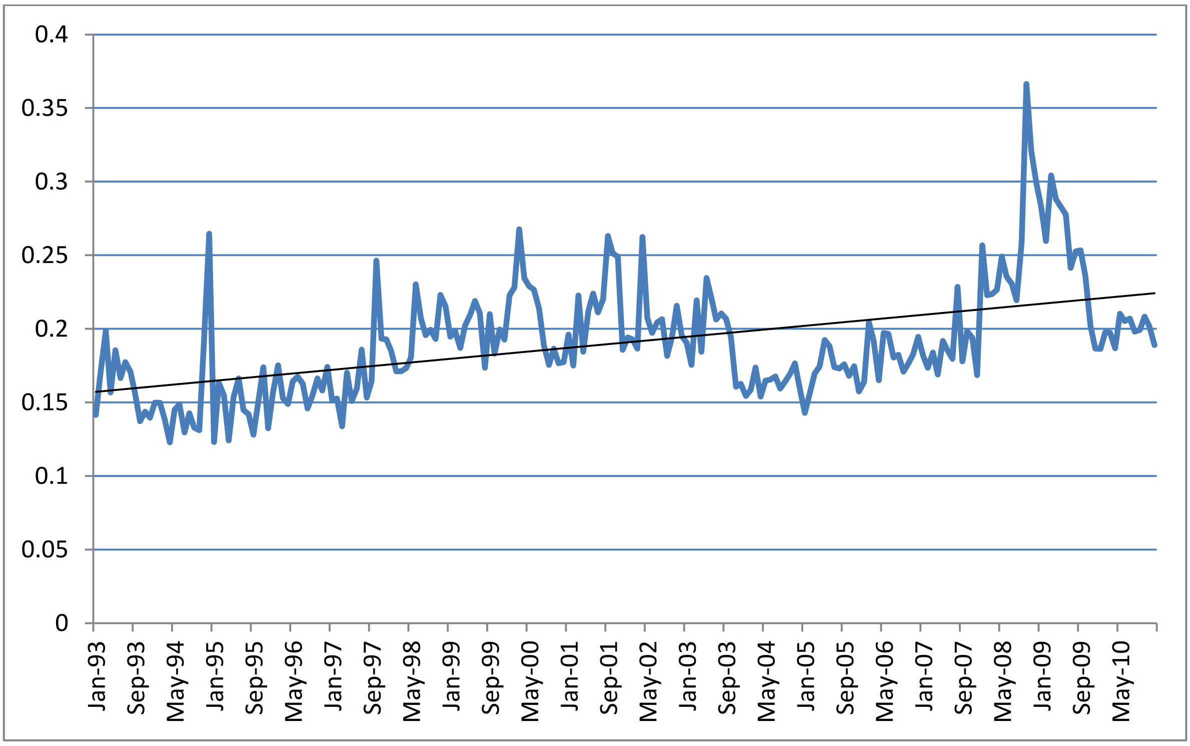
6.4.5. DISCUSSION FOR THE NEGATIVE RELATIONSHIP BETWEEN PAST RETURNS OF HIMLI PORTFOLIO AND FUTURE GROWTH RATE OF THE ECONOMIC INDICATORS

Generally, negative relationships between past one year returns of HIMLI portfolio and one year ahead growth rate of the economic indicators are observed. Positive relationships between past returns of the asset pricing factors and future growth rate of the economic indicators were expected. The reason is that current stock prices reflect investors' expectations on future earnings of the companies, and the earnings of the companies are highly correlated with the economic indicators. Therefore, high returns of the stock market factors should precede periods of high growth rate of the economic indicators. However, negative relationships between past returns of HIMLI portfolio and future growth rates of the economic indicators are observed. In order to explain the negative relationships between past returns of HIMLI portfolio and future growth rates of the economic indicators, the characteristics of idiosyncratic volatility are further discussed.

HIMLI is calculated as the returns of high idiosyncratic volatility stocks minus the returns of low idiosyncratic volatility stocks. In theory, idiosyncratic volatility is the level of unsystematic risk which is not diversified away in the portfolios. Investors require extra compensation for the existing idiosyncratic volatility in their portfolios. Previous studies suggest that idiosyncratic volatility increases significantly during bad stock market states but decreases marginally during good stock market states, for example, Ooi et al. (2009) suggest that behaviour of idiosyncratic volatility is asymmetric during different states of the stock market. Figure 6.1 confirms that the average idiosyncratic volatility of Australia stocks has asymmetric behaviour over the sample period.

Investors require higher returns to compensate the higher idiosyncratic volatility during bad stock market states, but investors require lower returns to compensate the lower level of idiosyncratic volatility during good stock market states. In addition, Chapter 3 of this thesis find that high idiosyncratic volatility stocks are small stocks and effect of idiosyncratic volatility is mostly pronounced by small stocks in Australia from 1993 to 2010 suggesting that idiosyncratic volatility of small stocks increases more than idiosyncratic volatility of big stocks during bad market state. Therefore, investors would expect that idiosyncratic volatility of the stocks will increase if investors expect that the economic state will enter bad state in the next period. Base on their expectation, they would require higher rate of return for the stocks in their portfolios. However, base on the finding reported in Chapter 3, idiosyncratic volatilities of small stocks is expected to increase more than idiosyncratic volatilities of the big stocks, so that required rate of returns for small stocks are also expected to increase more than those of the big stocks. Consequently, the difference between the return of high idiosyncratic volatility portfolio and the return of low idiosyncratic volatility portfolio is bigger precedes to periods of the bad stock market time than the difference precedes to periods of the good stock market time. Therefore, low (high) past returns of HIMLI precede good (bad) state of the future economy is observed in Table 6.7.

Figure 6.1 Time series of monthly average of idiosyncratic volatility from Jan/1993 to Dec/ 2010



6.5. CONCLUSION

Stock market information predicts economic activity as investors trade stock based on their expectations. Liew and Vassalou (2000) find that stock market return based asset pricing factors predict GDP growth rates in ten developed countries. Following Liew and Vassalou

(2000), this chapter investigates whether return based asset pricing factors, MKT, SMB, HML and HIMLI predict future growth rates of ten Australian economic indicators for the period 1993-2010 by using Australian stock market data.

The empirical findings contribute to the literature in several ways. First, a return based idiosyncratic volatility factor in added to Liew and Vassalou (2000) models. The results show evidence that the return based asset pricing factors, MKT and HML, have predictive power in relation to Australian economy growth, but the return based idiosyncratic volatility factor has very weak predictive power when considering the economic indicators in the presence of the Fama and French three-factor. The results support the notion that the return based idiosyncratic volatility is not a state variable in the context of Merton's (1973). Second, the portfolio performance analysis shows high returns of size and BE/ME portfolios precede periods of good states of economy, but high returns of idiosyncratic volatility portfolio precede periods of bad states of the economy. This negative relationship may be driven by the asymmetry behaviour of idiosyncratic volatility.

CHAPTER 7

7. CONCLUSION

7.1. INTRODUCTION

The role of unsystematic risk/idiosyncratic volatility in financial markets was almost ignored before the 1990's as the theory of CAPM suggests idiosyncratic volatility can be diversified by holding a large number of assets in a portfolio. Hence idiosyncratic volatility was not considered to play a significant role in asset pricing.

CAPM suggests that as long as investors hold well diversified portfolios, idiosyncratic volatility is not of concern. However, in reality, many investors do not hold well diversified portfolios due a number of factors, including transaction costs and/or limited knowledge/information relating to the assets available in markets. This implies that investors should require a higher rate of return for holding under diversified portfolios. Hence, idiosyncratic volatility should be priced for returns of risk assets. In addition, Campbell et al. (2001) suggest idiosyncratic volatility increases over time which implies that investors may need to increase the number of assets in their portfolios over time in order to maintain the same level of diversification. Therefore, the role of idiosyncratic volatility in financial markets is becoming increasingly important. Although some studies in the area of asset pricing role of idiosyncratic volatility have been undertaken in the past decade, but empirical results are mixed. Moreover, there is lack of research in area of idiosyncratic volatility for Australia. It is neither clear that idiosyncratic volatility plays an important role in pricing of Australian risky assets nor is it clear what drives or influences idiosyncratic volatility over time in Australian equity markets. This thesis provides an insight into the role of idiosyncratic volatility in Australian markets.

7.2. SUMMARY OF THE THESIS

The objective of this thesis is to investigate the role of idiosyncratic volatility in the content of Australia with an emphasis on the asset pricing role of idiosyncratic volatility. Specifically, the analysis undertaken in this thesis provides insights into (1) the relationship between idiosyncratic volatility and risky asset returns (in particular, Australian stocks and pension funds), (2) the information content of idiosyncratic volatility in regards to macroeconomic activities, and (3) the factors driving idiosyncratic volatility. These issues are addressed in the four empirical chapters of the thesis. The asset pricing role of idiosyncratic volatility for Australian stock returns is addressed in Chapter 3, the relationship between idiosyncratic volatility and Australian pension funds returns is investigated in Chapter 4, the driving factors of idiosyncratic volatility are explored in Chapter 5, and the information content of idiosyncratic volatility and other asset pricing factors is examined in Chapter 6.

The relevant literature is reviewed in Chapter 2. Based on the literature review, it is noted that there is a lack of research in the areas of idiosyncratic volatility in Australia. The majority of studies investigating the asset pricing role of idiosyncratic volatility use US data. Moreover, the empirical results of previous studies show mixed results as some studies find a positive relationship between idiosyncratic volatility and stock returns (see examples, Goyal and Santa-Clara,2003; Bali et al., 2005; Fu, 2009; Guo and Savickas,2010), while others report a negative relationship between idiosyncratic volatility and stock returns (see example, Ang et al., 2006). Hence it is not clear that what is the relationship between idiosyncratic volatility and risky asset returns, and this provides a primary motivation for this thesis.

Notwithstanding these mixed results, the majority of studies investigating the pricing of idiosyncratic volatility support the notion that idiosyncratic volatility is indeed priced. Hence, these findings provide motivation for this thesis to investigate the drivers of idiosyncratic volatility since it is important to understand what factors that explain this type of volatility.

Further, Liew and Vassalou (2000) find that asset pricing factors predict future economy growth. This provides motivation for the analysis undertaken in this thesis to investigate whether idiosyncratic volatility contains information in regard to the future economic growth of Australia.

The empirical analysis begins with Chapter 3, which investigates the asset pricing role of idiosyncratic volatility for Australian stocks. In this chapter, time series analysis, cross sectional analysis and the Fama and French (1993) risk mimicking portfolio approach are employed to address the issue. The empirical results suggest that idiosyncratic volatility is priced in both the time series and the cross-sectional analyses. The role of idiosyncratic volatility in asset pricing is examined by using 25 size and BE/ME sorted portfolios and 10 idiosyncratic volatility sorted portfolios. The empirical results suggest a positive relationship between idiosyncratic volatility and stock returns. The role of idiosyncratic volatility in asset pricing is further examined in different business cycles. Again, the empirical results show that idiosyncratic volatility is priced in both economic expansions and contractions, but indicate that the idiosyncratic volatility factor captures more variations in the stocks returns during economy expansions than contractions.

Chapter 4 examines whether idiosyncratic volatility is priced for Australian pension fund returns. Previous studies focus on the pricing of idiosyncratic volatility in relation to stock returns, but whether idiosyncratic volatility is priced in relation to managed fund returns has not been extensively tested. In this chapter, following the risk mimicking portfolio approach of Fama and French (1993), a pension fund size factor and an idiosyncratic volatility factor are constructed. The pension fund size factor is constructed by using historical pension fund size data to mimics the common risk related to pension fund size. The empirical results show that both the idiosyncratic volatility factor and the pension fund size factor are priced in Australian pension fund returns. However, when the pension funds are sorted into portfolios according to the Morningstar pension fund broad categories, the model captures more variation in the returns of equity funds than returns of fixed income funds. Further, the model captures greater variation in the returns of fixed income pension funds when a bond factor is included in the regression model.

Having established the importance of idiosyncratic volatility in the pricing of Australian stocks and Australian pension funds, Chapter 5 explores the factors that drive idiosyncratic volatility. This chapter was also motivated by Chang and Dong (2006), whose research found that profitability ratios explain idiosyncratic volatility in Japan. In this chapter, the relationship between stock fundamental ratios, such as profitability ratios, leverage ratios and valuation ratios, and idiosyncratic volatility is examined. The relationship is examined by using both portfolio analysis and regression analysis. The portfolio analysis results show that high idiosyncratic volatility companies tend to be small (measured by size), highly leveraged (measured by interest cover ratio), have low profitability (measured by ROE and earnings per share), be low in terms of valuation (measured by price to earnings ratio). The regression analysis results show that dividend yield is positively related to the idiosyncratic volatility. Also, the price-to-earnings ratio and ROE are negatively related to idiosyncratic volatility. The relationship between the idiosyncratic volatility and the stock fundamental ratios remains robustness in the presence of size.

Chapter 6 is the last empirical analysis chapter. This chapter investigates whether asset pricing factors, including the market factor, the size factor, the BE/ME factor and the idiosyncratic factor, predict economic growth in Australia by using the Liew and Vassalou (2000) model. The regression analysis in this thesis extends the literature by adding an idiosyncratic volatility factor into Liew and Vassalou (2000) model and using ten major economic indicators to represent different aspects of the Australian economy. The empirical results show that the market factor, the size factor, the BE/ME factor and the idiosyncratic factor predict eight out of ten major Australian economic indicators. The market factor contains most information about the future economic growth amongst the four asset pricing factors used in the analysis, while the idiosyncratic volatility factor contains the least amount of information about future economic growth.

7.3. KEY CONTRIBUTIONS

The studies in this thesis investigate the roles of idiosyncratic volatility in Australia. The asset pricing role of idiosyncratic volatility is first investigated by using a large sample of ASX listed companies and Australian pension funds. This thesis further explores the firm specific information factors that explain idiosyncratic volatility. Finally, this thesis examines the information content of the idiosyncratic volatility factor and other asset pricing factors in regard to future macroeconomic growth. The major contributions of this thesis are: (1) a new idiosyncratic volatility factor is constructed and tested in the pricing of Australian stocks, (2) a new pension fund size factor is constructed and tested in the pricing of Australian pension funds, (3) the idiosyncratic volatility factor is examined in its ability to predict future Australian economic growth, and (4) there is a relationship between idiosyncratic volatility and stock fundamental ratios in Australia.

Some of the major findings from each empirical chapter in this thesis are summarized below:

Chapter 3

- The idiosyncratic volatility factor is priced and positively related to Australian stock returns, and the explanatory power of the idiosyncratic volatility factor remains robust in both time series and cross-sectional analyses.
- Idiosyncratic volatility increases significantly during bad market times but decreases marginally during good market times.
- The idiosyncratic volatility factor is priced during economic expansions and contractions. However, the idiosyncratic factor captures greater variation in stock returns during economic expansions than contractions.

Chapter 4

- Idiosyncratic volatility is priced for the Australian pension fund returns.
- The pension fund size factor also captures variations in Australian pension fund returns.
- A three-factor model utilizing a market factor, a pension fund size factor and an idiosyncratic volatility factor captures greater variation in equity fund returns than in returns of other pension funds.

Chapter 5

- High idiosyncratic volatility companies tend to be small (measured by size), highly leveraged (measured by interest cover ratio), exhibit low profitability (measured by ROE and earnings per share), and low valuation (measured by price to earnings ratio).
- The dividend yield is positively related to idiosyncratic volatility. The price to earnings ratio and ROE are negatively related to idiosyncratic volatility. The relationship between the idiosyncratic volatility factor and Australian stock fundamental ratios remains robustness in presence of size.

Chapter 6

- The market factor, the size factor, the BE/ME factor and the idiosyncratic volatility factor predict the growth rates of eight major Australian economic indicators including the company gross profit index, CPI, the export price index, the effective foreign exchange rate, GDP, the import price index, the industrial production index and the unemployment rate index.

7.4. LIMITATIONS AND POSSIBLE FUTURE RESEARCH DIRECTIONS

The primary objective of this thesis is to investigate the roles of idiosyncratic volatility in the pricing of Australian risky assets. This thesis provides strong evidence to support that idiosyncratic volatility is important in the pricing of Australian stocks and pension funds, which provides the motivation to study the characteristics and underlying driving factors of idiosyncratic volatility.

A new method of constructing an idiosyncratic volatility mimicking factor is introduced in this thesis. This new method is inspired by, and developed based on, the risk mimicking portfolio approach of Fama and French (1993), and the idiosyncratic volatility definitions used by Ang et al. (2009) and Angelidis (2010). The idiosyncratic volatility factor (HIMLI) is constructed to mimic the risk factor in relation to idiosyncratic volatility.

The pricing ability of this idiosyncratic volatility factor is examined by using Australian data. Due to the insufficient number of stocks listed on the ASX in the early 1990's for portfolio construction purposes, two sample periods are used. For example, the first sample period for the ten idiosyncratic volatility sorted portfolios is from January 1993 to December 2010, but the sample period is shortened to January 2002 to December 2010 for the 25 size and BE/ME sorted portfolios. These sample periods are the longest possible sample periods that can be used in the studies undertaken in this thesis. Therefore, a longer sample period with data from different countries (for example, US data) could be an interesting and important extension to further test the robustness of the empirical results reported in this thesis.

In previous studies, alternative methods are used to measure idiosyncratic volatility. For example, idiosyncratic volatility can be measured as the difference between the stock's total risk and its systematic risk (see examples, Campbell et al., 2001; Drew, Naughton and Veeraraghavan, 2004), or it can be calculated as an expected value by using an EGARCH model (see example, Fu, 2009), as well as the risk mimicking approach adopted in this thesis. It is not yet clear which of these calculation methods, or definitions, gives the best idiosyncratic volatility measurement. This question could be addressed in future research.

It is shown in this thesis that idiosyncratic volatility increases significantly during good market times but decreases marginally during bad market times, and overall, idiosyncratic volatility increases over time. These findings are consistent with the results reported in studies of other countries. However, it is not clear what explains this asymmetric behaviour of idiosyncratic volatility. This question is left to future research.

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APPENDIX 1

Table A1 Conditioning Idiosyncratic Volatility Premia on Economy Conditions

$$r_t - r_{ft} = \alpha + \beta_0 (r_{mt} - r_{ft}) + \beta_1 D_{\text{expansion}} (r_{mt} - r_{ft}) + i_0 HIMLI + i_1 D_{\text{expansion}} HIMLI + \varepsilon_t$$

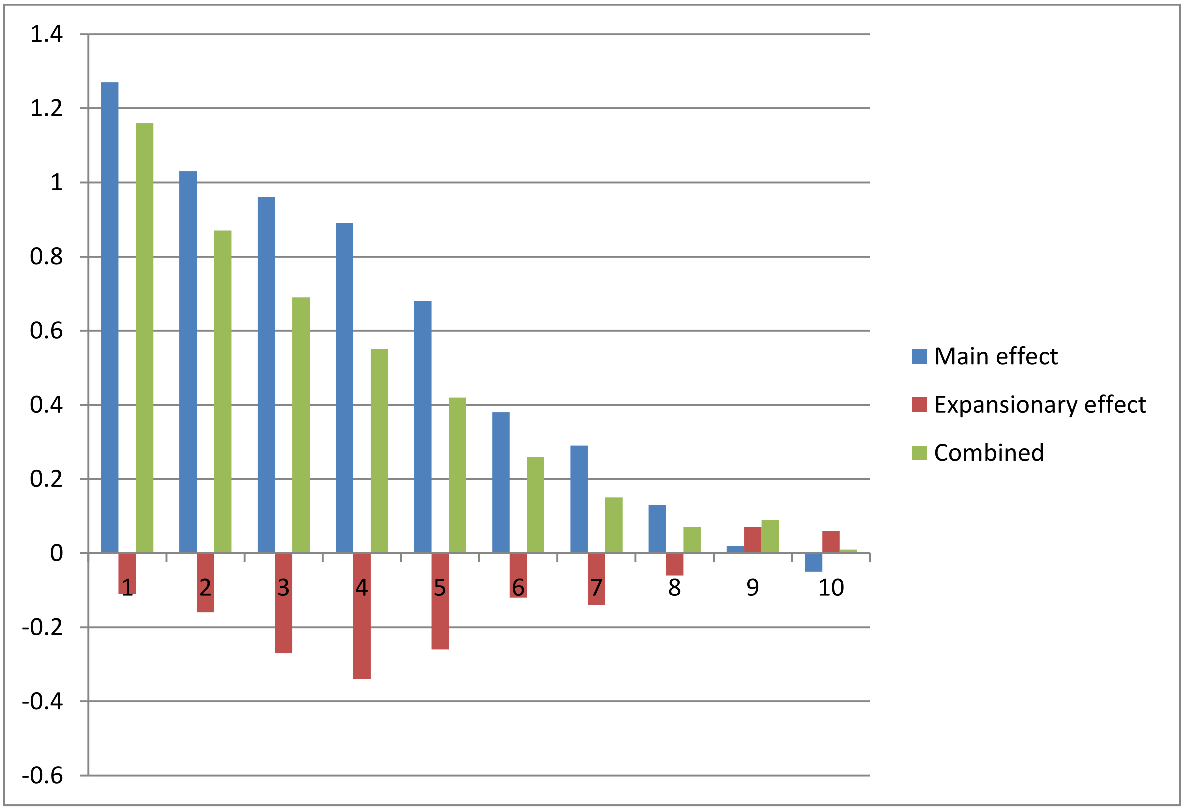
2-Factor Model

Expansions

Portfolio	Alpha	RMRF	D*RMRF	HIMLI	D*HIMLI	ADJ R-sq
1(high)	0.0209***	0.6301***	-0.1304	1.2270***	-0.1105	0.66
	4.43	3.04	-0.51	7.55	-0.63	
2	0.0003	0.7644***	-0.0586	1.0322***	-0.1573	0.75
	0.08	5.19	-0.33	8.94	-1.26	
3	-0.0002	0.6750***	0.1937	0.9550***	-0.2654**	0.71
	-0.06	4.73	1.11	8.54	-2.19	
4	-0.0028	0.6972***	0.1108	0.8876***	-0.3387***	0.68
	-0.92	5.18	0.67	8.41	-2.96	
5	-0.0016	0.6679***	0.1006	0.6800***	-0.2566**	0.66
	-0.61	5.69	0.70	7.39	-2.57	
6	-0.0025	0.9066***	-0.0623	0.3824***	-0.1163	0.67
	-1.05	8.85	-0.50	4.76	-1.34	
7	-8.37E-05	0.8318***	0.0099	0.2860***	-0.1404*	0.66
	-0.04	9.30	0.09	4.08	-1.85	
8	0.0025	0.8421***	-0.1385	0.1278*	-0.0562	0.57
	1.25	9.51	-1.28	1.84	-0.75	
9	0.0054***	0.7011***	-0.0808	0.0150	0.0682	0.52
	2.79	8.29	-0.78	0.23	0.95	
10(low)	0.0136***	0.4704***	-0.1641	-0.0475	0.0574	0.06
	3.60	2.85	-0.81	-0.37	0.41	

Note. Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the portfolios. RMRF is the excess return on the accumulative ASX All Ordinary Index, HIMLI is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model. $D_{\text{expansion}}$ is a dummy variable which takes a value of unity in the period if expansionary phase of the business cycle is identified by Melbourne Institute of Applied Economic and Social Research and a value of zero otherwise. The business cycle classification is downloaded from the website of the Melbourne Institute of Applied Economics and Social Research.

Figure A1 Plots of coefficients of $HIMLI$ and $D_{expansion}HIMLI$ from Table A1



Note. Blue bars represent the coefficients of $HIMLI$ and Red bars represent the coefficient of $D_{expansion}HIMLI$ from Table 1 in the Appendix. Green bars represent the combined effect. The horizontal axis represents the ten portfolios sorted on idiosyncratic volatility. Portfolio 1 consists of stocks with highest idiosyncratic volatility and portfolio 10 consists of stocks with lowest idiosyncratic volatility. The patterns in the Blue and Green bars are consistent with the results reported in Table 16 of Chapter 3 as the returns of higher idiosyncratic volatility stocks are more sensitive to the idiosyncratic volatility factor $HIMLI$ than the returns of lower idiosyncratic volatility stocks. During expansion, the returns of the portfolios are lower during expansions than the returns of the portfolios during contractions as the coefficients of $D_{expansion}HIMLI$ are generally negative. The results suggest that effect of idiosyncratic volatility is significant over different phases of economy.

APPENDIX 2

Table A2 Variable definitions

Variable	Definition
SIZE	market capitalization of the company, it is displayed in millions of unites of Australian dollar
BE/ME	book to market equity ratio
Idiovol	idiosyncratic volatility is the standard deviation of the regression residual of an asset pricing model
RMRF	excess return of the market portfolio over the risk free rate
SMB	size factor, calculated as returns of the small company portfolio minus returns of the big company portfolio
HML	BE/ME factor, calculated as returns of the high BE/ME portfolio minus returns of the low BE/ME portfolio
HIMLI	the idiosyncratic volatility factor, calculated as returns of the high idiosyncratic volatility portfolio minus returns of low idiosyncratic volatility portfolio
R_{bondt}	return of UBS Warburg bond index
dividend yield	dividend yield of the company expresses the dividend per share as a percentage of the share price
Icover	interest cover ratio is defined as earnings before interest and tax/interest expenses on debt less interest capitalised
Size	market capitalization of the company
PE	price to earnings ratio, calculated as the price divided by the earnings rate per share at the required date
ROE	return on equity
EPS	earnings per share is the earnings per share of a company
Company profit	company gross operating profit index
CPI	consumer price index measures quarterly changes in the price of a basket of goods and services
EXPORT	export price index includes prices obtained from major exporters
Effective exchange rate	effective exchange rate index, calculated by Reserve Bank of Australia
GDP	gross domestic production is the total market value of goods and services produced in Australia within a given period
IMPORT	import price index covers about 95% of merchandise imported during the sample period
IP	industrial production
M1	money supply is defined as currency plus bank current deposits of the non-bank private sector
T-BOND	treasury bond rate measures the yield on long term government bond on the secondary market
Unemployment	unemployment rate